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GIS Analysis of Spatial Clustering and Temporal Change in Weeds of Grass Seed Crops

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Ten years of Oregon Seed Certification Service (OSCS) preharvest field inspections converted from a nonspatial database to a geographic information system (GIS) were analyzed for patterns in spatial distribution of occurrence and severity of the 36 most common weeds of grass seed crops. This was done under the assumptions that those patterns would be primarily consequences of interactions among farming practices, soil properties, and biological traits of the weeds, and that improved understanding of the interactions would benefit the grass seed industry. Kriging, Ripley's K-function, and both Moran's I spatial autocorrelation and Getis-Ord General G high/low clustering using the multiple fixed distance band option all produced roughly similar classifications of weeds possessing strongest and weakest spatial clustering patterns. When Moran's I and General G analyses of maximum weed severity observed within individual fields over the life of stands were conducted using the inverse distance weighting option, however, results were highly sensitive to the presence of a small number of overlapping fields in the 10-yr record. Addition of any offset in the range from 6 to 6,437 m to measured distances between field centroids in inverse distance weighting matrices removed this sensitivity, and produced results closely matching those for the multiple fixed distance band method. Clustering was significant for maximum severity within fields over the 10-yr period for all 43 weeds and in 78% of single-year analyses. The remaining 22% of single-year cases showed random rather than dispersed distribution patterns. In decreasing order, weeds with strongest inverse-distance spatial autocorrelation were German velvetgrass, field bindweed, roughstalk bluegrass, annual bluegrass, orchardgrass, common velvetgrass, Italian ryegrass, *Agrostis* spp., and perennial ryegrass. Of these nine weeds, distance for peak spatial autocorrelation ranged from 2 km for *Agrostis* spp. to 34 km for common velvetgrass. Weeds with stronger spatial autocorrelation had greater range between distance of peak spatial autocorrelation and maximum range of significance. Z-scores for General G high/low clustering were substantially lower than corresponding values for Moran's I spatial autocorrelation, although the same two weeds (German velvetgrass and field bindweed) showed strongest clustering using both measures. Simultaneous patterns in Moran's I and General G implied that management practices relatively ineffective in controlling weeds usually played a greater role in causing weeds to cluster than highly effective practices, although both types of practices impacted Italian ryegrass distribution. Distance of peak high/low clustering among perennial weeds was smallest (1 to 3 km) for Canada thistle, field bindweed, *Agrostis* spp., and western wildcucumber, likely indicating that these weeds occurred in patchy infestations extending across neighboring fields. Although both wild carrot and field bindweed doubled in average severity over the period from 1994 to 2003, wild carrot was the only weed clearly undergoing an increase in spatial autocorrelation. Soil chemical and physical properties and dummy variables for soil type and crop explained small but significant portions of total variance in redundancy and canonical correspondence analysis of weed occurrence and severity. Fitch-Morgoliash tree diagrams and Redundancy Analysis (RDA) and Canonical Correspondence Analysis (CCA) ordinations revealed substantial differences among soil types in weed occurrence and severity. Gi* local hot-spot clustering combined with feature class to raster conversion protected grower expectations of confidentiality while describing dominant spatial features of weed distribution patterns in maps released to the public.

Nomenclature: Annual bluegrass, *Poa annua* L. POAAN; Canada thistle, *Cirsium arvense* (L.) Scop. CIRAR; common velvetgrass, *Holcus lanatus* L. HOLLA; field bindweed, *Convolvulus arvensis* L. CONAR; German velvetgrass, *Holcus mollis* L. HOLMO; Italian ryegrass, *Lolium multiflorum* Lam. LOLMU; orchardgrass, *Dactylis glomerata* L. DACGL; perennial ryegrass, *Lolium perenne* L. LOLPE; roughstalk bluegrass, *Poa trivialis* L. POATR; western wildcucumber, *Marah oreganus* (T. & G.) T. J. Howell ECNOR; wild carrot, *Daucus carota* L. DAUCA.

Key words: Moran's I spatial autocorrelation, Getis-Ord General G high/low clustering, Getis-Ord Gi* hot spot analysis, kriging.

Use of geostatistics to analyze spatial and temporal properties of weeds is an active area of research, with increased weed management efficiency commonly cited as the primary anticipated benefit (Clay et al. 2006; Colbach et al. 2000; González-Andújar et al. 2001; Jurado-Expósito et al. 2003; Wiles and Schweizer 2002; Wyse-Pester et al. 2002). In most cases, focus has been on patchiness of weeds within individual fields; data were acquired using grid sampling procedures, and kriged maps of weed distribution/density were typical end products (Cardina et al. 1995; Donald 1994; González-Andújar et al. 2001; Johnson et al. 1996; Jurado-Expósito et al. 2003; Wiles and Schweizer 2002; Wyse-Pester et al. 2002). Several researchers have extended their geospatial analyses into associations among weeds and site characteristics such as irrigation practices, soil chemistry, soil physical properties, elevation, and moisture (Dieleman et al. 2000a,b; McElroy et al. 2005; Wiles and Brodahl 2004). Comparisons over time have evaluated the stability of weed patches as a major determinant of the usefulness of weed maps in tailoring herbicide applications for precision agriculture (Clay et al. 2006; Colbach et al. 2000). Numerous studies have centered on the consequences of sampling methods, interpolation procedures, and general statistical assumptions in mapping of weeds and interpretation of results (Cardina et al. 1995; Cousens et al. 2002; Dale 1999; Dille 2002; Johnson et al. 1996; Wiles and Schweizer 2002).

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General shortage of geospatial data on weeds is widely recognized as the primary factor limiting weed scientists' abilities to conduct analyses identifying management practices and edaphic factors controlling behavior of these pests across landscapes and over management practices (Dieleman et al. 2000a,b; Donald 1994; Wiles and Brodahl 2004). Remote sensing has been explored as one way to collect spatial data on weeds in a more cost-effective manner than the traditional, labor-intensive, grid-sampling method (Lass and Callihan 1997; Lass et al. 1996; Medlin et al. 2000). Common elements of nearly all previous research have been a focus on within-field mapping of weed patches and the relatively small number of separate fields generally studied. In our analysis of OSCS field inspection reports for grass seed crops of Linn County, OR, we have, at least temporarily, abandoned concern over within-field variability and broadened the focus of our analyses to the landscape level to better understand the behavior of weeds in an entire agricultural industry. In addition to expanding the physical scale at which weeds are studied, we have expanded the analytical tools to include not only kriging and other interpolation methods but also a series of cluster analysis procedures. As a consequence of the broader range of inference possible when an entire industry is examined, we anticipate our findings will improve the efficiency of weed control efforts by farmers, and also support better-informed research planning by weed scientists and decision-making by regulatory agencies that manage activities ranging from plant quarantine enforcement to herbicide registration. Two major hurdles we faced in analyzing the GIS developed from the OSCS field inspection reports were: (1) initial unfamiliarity with geostatistical procedures for identifying patterns and locating clusters in data, and (2) the need to properly incorporate the effects of spatial autocorrelation while analyzing relationships between geographic features using more familiar tools such as analysis of variance or regression. The approach we have developed is detailed in this manuscript, along with the vision that approach has provided of the behavior of weeds across an entire industry. Many specialized agronomic practices are used in grass seed production, including carbon-band planting, postharvest residue management (field burning, baling, and chopping of full straw load), early fall application of pre-emergence herbicides to established stands of perennial crops, and mid-fall through early spring application of marginally selective herbicide treatments that control young seedling weeds while damaging but generally not killing established perennial crop plants (Lee 1966, 1973, 1981; Mueller-Warrant 1990, 1999; Mueller-Warrant et al. 1991; Mueller-Warrant and Neidlinger 1994; Mueller-Warrant and Rosato 2002, 2005). Concerns over seed purity in grass seed crops often outweigh issues of yield loss from weed–crop competition or damage from herbicide treatments.

Because of the importance that spatial autocorrelation plays in potential modifications of familiar analytical procedures, in addition to its central role in identifying locations of clusters, proper analysis of spatial autocorrelation is central to successful statistical analysis of geospatial data. Moran's I and Geary's c are global measurements of the overall pattern of spatial autocorrelation displayed by numerical data, and test hypotheses that similar values tend to cluster together, be randomly distributed, or be dispersed more evenly across an area than would be expected by chance (Mitchell 2005). Global Moran's I is calculated as

$$I = n\sum_i\sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x}) \div \sum_i\sum_j w_{ij}\sum_i (x_i - \bar{x})^2,$$

where n is the number of features, x_i is the value of feature i, x_j is the value of feature j, $\bar{x}$ is the mean value of all features, and w_{ij} is the weight assigned to each pair of features x_i, x_j (Mitchell 2005). The expected value of Moran's I for randomly distributed values is $I_E = -1 \div (n - 1)$, which becomes close to 0 for large n. If pairs of observations more often have similar rather than dissimilar values, Moran's I is greater than 0, indicating that similar values are clustered. Conversely, if more pairs have dissimilar rather than similar values, Moran's I is less than 0, indicating that values are dispersed. Possible values for Moran's I range from -1 to 1. Statistical significance of Moran's I is tested using a Z-score calculated as the difference between the observed and expected values for Moran's I divided by the standard deviation of the expected Moran's I for randomly distributed values (Mitchell 2005; Schabenberger and Gotway 2005). The Getis-Ord General G high/low clustering statistic not only tests for whether clustering has occurred, but also tests specifically for whether above-average or below-average values cluster more strongly. General G high/low clustering is calculated as

$$G = \sum_i\sum_j w_{ij}(x_i \cdot x_j) \div \sum_i\sum_j (x_i \cdot x_j),$$

where x_i is the value of feature i, x_j is the value of feature j, and w_{ij} is the weight assigned to each pair of features x_i, x_j (Mitchell 2005). The expected value for Getis-Ord General G for randomly distributed values is $\sum_i\sum_j w_{ij} \div n(n - 1)$. Large positive values for General G indicate that higher than average values are clustered, whereas large negative values indicate that lower than average values are clustered. Statistical significance of Getis-Ord General G is tested using a Z-score calculated as the difference between the observed and expected values for General G divided by the standard deviation of the expected General G for randomly distributed values (Mitchell 2005). If both high values and low values tend to cluster, General G will be positive if there are more high values than low values, and negative if there are more low values than high values. The weight matrix w_{ij} for both Moran's I and Getis-Ord General G can take on a number of common forms. If $w_{ij} = 1$ for all distances less than some critical threshold and $w_{ij} = 0$ beyond that distance, then the weighting procedure is referred to as a fixed distance band. If w_{ij} is inversely proportional to the distance between pairs of points, then the weighting procedure is referred to the inverse distance method. Spatial statistics can be viewed as an extension of traditional (nonspatial) statistics to primarily deal with the problem of violation of the assumption of independence among samples. Various methods of spatial statistics explicitly model spatial autocorrelation and can correct the degrees of freedom in significance tests for the lack of complete independence among closely spaced points. In order to do so, however, other assumptions must be made about the data, violations of which have their own consequences. One common assumption is stationarity, or the absence of strong, long-distance trends in the data. When this assumption is violated, procedures such as Moran's I and Getis-Ord General G report that spatial autocorrelation and clustering exist, but they fail to convey possibly far simpler underlying explanations for the correlation, such as a long distance north–south or east–west trend in the data. If spatial autocorrelation and clustering are strictly defined to exclude simple long distance trends, then violation of stationarity can compromise the validity of statistical tests for spatial autocorrelation (Brownie and Gumpertz 1997). However, simulation studies we conducted showed that the primary consequence of adding long distance trends (i.e., violating stationarity) to data with known hot spots was reduced ability to detect the hot spots in areas where the long distance trends were strongest (data not shown).

Once the presence of global patterns has been confirmed, local versions of Moran's I and Getis-Ord G statistics provide statistical evidence for the presence of clusters that differ from expected values at specific locations. Other measurements commonly used to evaluate clustering of events include quadrat analysis, nearest neighbor index, and K-function (Dale 1999; Mitchell 2005). These latter three statistical measurements, however, typically incorporate only the spatial distribution of points and not the magnitude of observations at those points, and hence can tend to provide less powerful tests of spatial autocorrelation for data such as a weed severity index in the OSCS field inspections. Local Getis-Ord Gi* is calculated as $G_i^* = \sum_j w_{ij} x_j \div \sum_j x_j$, where i is the point at which Gi* is being calculated, x_j is the value of feature j, and w_{ij} is the weight assigned to each pair of features x_i, x_j (Mitchell 2005). The weight matrix w_{ij} can assume any of the forms described above for use in global Moran's I and Getis-Ord General G calculations. The expected value of Gi* for randomly distributed values is $E(G_i^*) = \sum_j w_{ij} \div (n-1)$. A group of features with high Gi* values is indicative of a cluster of features with high attribute values, or a hot spot, a group with low (large negative) Gi* values is a cold spot, and points with Gi* values close to zero are viewed as neither. Statistical significance of Gi* for randomly distributed values is tested using a Z-score calculated as the difference between the observed and expected values for Gi* divided by square root of the variance of Gi* for all features (Mitchell 2005). Statistical concerns that exist regarding use of local Gi* include: (1) edge effects, where points near boundaries of the study area have fewer neighbors than points in the interior, exaggerating similarities and differences; (2) skewing of the distribution by outliers when small numbers of features are being analyzed, typically viewed as fewer than 30 points; (3) diminished ability to detect individual clusters when strong global patterns are present; and (4) distortion of the confidence level in Z-tests due to lack of independence between features. The confidence level issue is conceptually similar to multiple comparisons problem in traditional analysis of variance, and Bonferroni-style corrections that attempt to control the chance of making any single Type I error within the whole set of multiple comparisons do so at the expense of increasing the frequency of Type II errors. Schabenberger and Gotway (2005) summarize the current view by statisticians of local indicators of spatial autocorrelation (LISA) in the following statements: (1) "The exact distributional properties of the autocorrelation statistics are elusive" and (2) "It is not clear how to adjust individual Type-I error levels to maintain a desired overall level." Despite this ambiguity by statisticians in their view of LISAs, Mitchell (2005) leaves little room for doubt in his description of the most incontrovertible feature of spatial statistics when he says, "it's not uncommon in the GIS setting to find yourself working with very large datasets. Obtaining statistical significance in these cases will not be difficult if you're analyzing several thousand features or more."

Our choice of Moran's I and Getis-Ord General G global statistics and Gi* hot-spot analysis local statistics to analyze spatial patterns of weed occurrence and severity does not mean that we believe other techniques, such probability mapping in kriging, if properly conducted, would not also lead to similar interpretations of weed behavior. Our choice simply meant that we believed the Gi* hot-spot analysis method in particular could successfully extract the most important features of our complex dataset. The set of tools for analyzing spatial patterns within the ArcGIS environment expanded greatly over the period of time in which we conducted this research in a series of new product releases from Environmental Systems Research Institute (ESRI). Methods exist for exporting data from ArcGIS into other programming environments, including spreadsheets such as Microsoft Excel, statistical packages such as R and SAS, and high-level languages such as Python. Portions of our analyses were conducted in a number of these alternative environments, sometimes to overcome limitations built into ArcGIS and sometimes merely to verify the validity of our results.

Our broad objective was to analyze spatial distribution patterns in occurrence and severity of the 36 most commonly occurring weeds in preharvest inspections of certified grass seed crops conducted by the OSCS under the assumption that any patterns present would be the result of interactions over time among farming practices, soil properties, and innate biological traits of the weeds. It is our hope that improved understanding of those interactions will benefit the grass seed industry in its ongoing struggle to control weeds. Because these analyses were done both with and without inclusion of information on the location of seven of those weeds when they were also grown as crops, we actually analyzed 43 cases. Our specific objectives were to: (1) determine whether the global distribution patterns of occurrence and severity of common weeds of grass seed crops in Linn County, OR, were clustered, dispersed, or random; (2) for weeds with clustered distribution patterns, determine whether the more severe infestations or relatively weed-free fields were more strongly grouped; (3) characterize possible changes over the 10-yr period in clustering patterns of grass seed weeds; (4) map local hot spots of strongly clustered weeds in a format suitable for release to the general public without violating OSCS promises of confidentiality to the growers; and (5) identify edaphic characteristics and crop management practices linked to location of these hot spots.

Materials and Methods

GIS Data Sources. A more complete description of procedures used to acquire and georeference data on the severity and spatial distribution of weeds in OSCS records of preharvest field inspections will be provided in another manuscript currently under preparation. In brief, information in a nonspatial database of the OSCS was exported as a series of text files using a web browser interface, imported into Microsoft Excel spreadsheets, manipulated into more convenient data formats, and imported into an ArcGIS personal geodatabase. Within ArcGIS, information from the OSCS records were combined with common land unit (CLU) polygons from USDA–Farm Service Administration (FSA), Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) imagery, and ground-truth data to create a georeferenced database of cropping patterns and weed severity indices from 1994 to 2003 for 10,643 harvests from 2,779 distinct certified grass seed fields in Linn County, OR. Six nearby fields in neighboring counties were included in the geospatial analysis. Although field shapes were kept constant for all years of production of a given certified stand, field shapes often changed through merger or subdivision of fields during rotations from one certified stand to the next. When all fields present over the 10-yr period were displayed on a single map, it became possible for individual fields to partially overlap and their centroids to fall at arbitrarily close distances to one another. Access to the OSCS database had been granted under provision that no confidential business information would be publicly released. Maximum weed severity values occurring throughout the life of individual grass seed stands were extracted from the individual year data. In addition to values of 0, 0.75, 1.75, and 2.75, which denoted the *absence* of a weed or its presence at *trace*, *many*, or *excessive* levels, respectively, we added a value of 3.75 to handle the case of species previously grown as a crop (e.g., Italian ryegrass and Kentucky bluegrass [*Poa pratensis* L. POAPR]). The severity index corresponded approximately to logarithmic differences in plant density (R. Cook 2003, personal communication). Justification for selecting these particular values to transform the ordinal data into interval data is given below in the "Statistical Analyses" section of Materials and Methods and in the "Year-to-Year Changes in Severity of Weeds in Established Grass Seed Stands" section of Results and Discussion.

Soil Survey Geographic Database soil data was obtained from the USDA–NRCS Soil Data Mart at http://soildatamart.nrcs.usda.gov/ on March 25, 2006 for Benton, Lane, Linn, Marion, Polk, and Yamhill counties of western Oregon. Data from each county were converted to a more limited, standardized set of soil names by pooling soil types that differed only in slope, and counties were merged to create a single shapefile of western Oregon soils using uniform soil type names. This shapefile was clipped by field polygons from the grass seed cropping database, and the areas of the 9,760 resulting polygons were calculated. Physical and chemical characteristics of these soil types were obtained from Benton County data when available and otherwise from Linn, Lane, or Marion county data. Data were exported in text file format and imported into Microsoft Excel to identify subsets of soil types covering a minimum of 5, 10, or 21% of the area of each individual field, along with identifying the single most common soil type present in each field. In the most extreme case, the majority soil type covered only 21% of a single field's total area. Weed severity values from each individual field were assigned to all soil type polygons derived from that field.

Statistical Analyses. Validity of our conversion of weed severity scores from ordinal to interval data type was evaluated by several procedures in line with fundamental principles of statistics as described by Steele et al. (1997), and in particular the ability of logarithmic transformations to normalize variances that otherwise tend to increase with increasing means (Box 1988). First, we carefully considered statistical implications of possible violations of the equal spacing requirement that similar differences between pairs of data values have similar meaning for all pairs in interval data. Second, we tested for normality of data using an initial logarithmic range conversion of 0, 1, 2, 3, and 4 for *absence* of a weed, presence at *trace*, *many*, and *excessive* levels, and production as a crop, and alternate conversions from ordinal to interval data using different distances between the weed severity ratings, particularly between *absence* of a weed and its presence at *trace* levels. Reasons for our final selection of 0, 0.75, 1.75, 2.75, and 3.75 as the best values for conversion from ordinal to interval data are provided below in the Results and Discussion section. Third, we directly observed the rating process for a number of weeds in preharvest field inspections, simultaneously making our own visual ratings of ground cover and stand density of those weeds and noting the approximately exponential differences in ground cover (or stand density) between cases in which weeds were rated as occurring at *trace*, *many*, and *excessive* levels.

Weed severity values from each individual year were analyzed in some cases, although most of our analyses were conducted on the maximum severity observed over the entire 10-yr period within individual fields. Preliminary analyses conducted using both 10-yr average severity and 10-yr maximum severity revealed very little difference between the two methods of pooling over time, mainly because most of the nonzero observations were simply detections at the *trace* level. Spatial clustering was characterized using both Moran's I spatial autocorrelation and Getis-Ord General G high/low clustering procedures of ArcGIS. Both procedures require that observations at any one location be single valued, and they convert polygons to centroids if spatial data type is polygon rather than point. For both measures of clustering, inverse distance weighting and fixed distance weighting methods were used to define spatial neighborhoods (Mitchell 2005). In addition to the distance weighting options available within ArcGIS, we have followed Mitchell's (2005) suggestion and modified the inverse distance weighting matrices by addition of a series of arbitrary offsets to the calculated distances between polygon centroids before taking the inverse. If D_{ij} is the Euclidean distance between points i and j, SO is the arbitrary spatial offset being introduced, and w_{ij} is the weight matrix for use in Moran's I, Getis-Ord General G, and Gi* calculations, then $w_{ij} = 1 \div (D_{ij} + SO)$, which reduces to simple inverse distance weighting when SO = 0. Spatial offsets tested ranged from 0.3 to 12,875 m in factors of two. Python scripts used to convert the raw spatial distance matrix exported from ArcGIS into modified inverse distance matrices are available online at http://www.ars.usda.gov/pandp/people/people.htm?personid=4006. Regression of spatial autocorrelation and high/low clustering vs. logarithm of offset distance was conducted in R version 2.6.0 (R Development Core Team 2007; available online at http://www.r-project.org/) using a linear model that included main effects of weed species and third or second degree polynomial logarithmic offset distances, respectively. The Vegan package in R was used to conduct principal component and other multivariate analyses.

Chi-square tests for independence vs. interaction of weed species and soil type as classification factors in contingency tables were used to determine the need for presenting full matrices rather than mean values for each weed species or soil type (Steel et al. 1997). Chi-square tests were conducted using three weed severity reclassification categories (*absent*, present only at *trace* levels, or present at greater than *trace* levels) and also using just two categories (absent vs. present at any level). In the interest of space, only results for the presence vs. absence of weed species within soil types are being reported. Also in the interest of space, only results for soil types covering at least 21% of the area within any field are being reported. Soil types infrequently present in grass seed fields whose chi-square tests for freedom from interaction with any of the 43 weeds were nonsignificant have also been excluded from our summaries. PHYLIP (Phylogeny Inference Package) ver. 3.65 available at http://evolution.gs.washington.edu/phylip.html was used to generate Fitch-Margoliash tree diagrams of dissimilarity of weed occurrence at any level in 36 soil types averaged over weed species and dissimilarity of 35 weed species averaged over soil types using the Global search option. Multivariate analyses in R of weed occurrence and severity are presented as bi-plot ordinations and as comparison of models in table format.

Hot spot Localization. We generated local Getis-Ord Gi* hot-spot maps of weed severity clusters for all 43 weeds using fixed distance neighborhoods set equal to the distance of peak clustering of the global Getis-Ord General G statistic (Mitchell 2005). For weeds in which peak clustering distance was less than 4 km we used a distance range of 4 km to minimize the potential for disclosure of the actual inspection report findings on individual fields, which are viewed by the seed industry as confidential business information. To further protect confidentiality of grower data in final maps, we degraded their spatial resolution by assigning Gi* values to centroids rather than polygons, converting from points to rasters by inverse distance weighting (power = 1, number of neighboring points = 12) interpolation, and clipping the rasters by 1.61 km buffers around original fields, omitting buffer regions in which there was only a single field. Additional protection of grower privacy was provided by identifying 16 fields at which fewer than seven points fell within the 4 km minimum fixed distance band used in the Gi* calculation, and masking buffers halfway from these points to areas with denser data. Rasters of probability that weed severity was significantly lower or higher than average were clipped to the publicly available 1999 Oregon Current Wildlife Habitat (http://www.nwhi.org) raster for agricultural land and urban areas to omit areas of other landuses, primarily forests and riparian zones.

Results and Discussion

Year-to-Year Changes in Severity of Weeds in Established Grass Seed Stands. Year-to-year changes in weed severity provided the best opportunity to test the normality (and other statistical properties) of our conversion of OSCS inspection ratings of *absent*, *trace*, *many*, *excessive*, and grown as crop into interval data. We initially tested conversion from ordinal to interval data using values of 0, 1, 2, 3, and 4 for the five classes. Such a transformation is in line with procedures noted by Kenkel et al. (2002) as being "appropriate in cases where a biological population (e.g., a weed newly introduced into a field) is capable of exponential increases in cover abundance." Logarithmic transformations are also useful in achieving normality in cases where effective herbicide treatments lower weed populations by exponential factors compared to untreated checks or plots invaded by herbicide-resistant weeds (Mueller-Warrant et al. 2007). Examination of year-to-year changes in severity of weeds within individual fields calculated using this initial conversion scale revealed some relatively minor abnormality in the distribution of data. Testing of a range of alternate conversion scales identified the need to reduce spacing between values representing *absent* and present at a *trace* compared to distances between each of the remaining classes. Optimal conversion scales to provide normality in the data varied for each individual weed, but results for four of the most serious ones, Italian ryegrass, annual bluegrass, roughstalk bluegrass, and Canada thistle, averaged to a factor of 0.75 for the ratio of the distance between *absent* and present at a *trace* vs. distances between each of the other classes in order. This generated a conversion scale of 0, 0.75, 1.75, 2.75, and 3.75 for ratings of *absent*, *trace*, *many*, *excessive*, and grown as a crop that was then used for all weed species. Comparison of results using the initial 0, 1, 2, 3, and 4 conversion scale and the final 0, 0.75, 1.75, 2.75, and 3.75 conversion scale revealed no major changes in interpretation or statistical significance of regressions of weed occurrence or severity over time and between stands (data not shown). Similarly, maps of weed severity hot-spot probability produced using both conversion scales were nearly identical (maps using initial 0, 1, 2, 3, and 4 conversion scale are not shown). When data were represented using linear scales for severity (e.g., 0, 0.1, 1, 10, 100) rather then the logarithmic transformation ultimately selected, analyses and maps were dominated either by the few cases in which weeds were rated as *severe* or by the inclusion of fields in which species were grown as crops (data not shown). As a consequence of the domination of linear scales by outliers, many analyses that were statistically significant using the logarithmic conversion scale were nonsignificant using linear representations of severity.

Nearly half of the grasses and two-thirds of the broadleaf weeds increased in occurrence and severity over the period from 1994 to 2003 (data not shown). The most rapidly increasing grasses included roughstalk bluegrass, rattail fescue [*Vulpia myuros* (L.) K. C. Gmel. VLPMY], and annual bluegrass, while most rapidly increasing broadleaves included Canada thistle, field bindweed, groundsel, wild carrot, Himalaya blackberry (*Rubus discolor* Weihe & Nees RUBDI), and prickly lettuce (*Lactuca serriola* L. LACSE) (data not shown). The most common change was for a field to transition from having no detections of these weeds in the earlier years of this time period to having detections at the *trace* level in the later years. For roughstalk bluegrass, field bindweed, and Canada thistle, however, ratings at the *many* level also increased in frequency, especially from the beginning to the middle of the period, years that coincided with a mandatory phase-down in field burning. Regression of field bindweed and wild carrot severity over time indicated that these two species more than doubled in average severity from 1994 to 2003 (data not shown).

Exploratory Analysis of Spatial Data. Exploratory data analysis and presentation methods applied to weed severity scores included inverse distance weighting (IDW) interpolation and ordinary kriging, both of which convert point data representing conditions at field centroids into raster prediction surfaces covering both field polygons and areas between fields. IDW on weed severity within individual years or on maximum severity observed within fields over the 10-yr period generally produced complex rasters with many striking ''bull's-eye'' features centered on individual fields. The bull's-eyes occurred whenever individual fields with nonzero severity for particular weed species were surrounded by fields with no detections of that weed. Because IDW is an exact interpolator at points from which the rasters are generated, maps created using this procedure could in theory be converted back to actual values at field centroids and thereby risked violating grower expectations of data confidentiality. IDW maps of weed severity were also unsuited to our purposes because they were often highly variable at small spatial scales, tending to obscure larger scale trends in the ''noise'' among neighboring fields. After rejecting use of IDW, ordinary kriging was next evaluated as a means to analyze data and produce maps suitable for public release. Unlike IDW, kriging can produce both an interpolated prediction surface and a matching probability surface. Because the interpolated values need not exactly match the original point values, kriging prediction surfaces could protect confidentiality of individual field data. Although kriging is a powerful method for potentially extracting significant spatial trends in data, it is also quite complex and involves selection of models for the empirical semivariogram and setting of numerous parameters, including lag distance, bin size, and anisotropy. Kriging achieves computational efficiency in calculating spatial autocorrelation by grouping points into relatively small numbers of bins of integer multiples of the lag distance, but because of this binning the empirical semivariogram in kriging is only an approximation of the true spatial autocorrelation. Primary features of interest in the empirical semivariogram are the nugget, partial sill, sill, and range, where the nugget represents microscale variation and/or measurement error, the sill represents variance in the data at distances beyond the range of spatial autocorrelation, the partial sill is the difference between the sill and the nugget, and the range represents the maximum distance over which values are spatially autocorrelated. Kriging of maximum weed severity observed within fields over the 10-yr period using ArcGIS default parameters revealed nonzero partial sills for 35 of 43 weeds, suggesting that spatial autocorrelation existed for most, but perhaps not all, weeds. Ratio of partial sill to sill was greatest in German velvetgrass at 0.75, and exceeded 0.2 in 22 cases. Range exceeded the distance between the two most widely separated fields for 15 of the 43 weeds, suggesting that either spatial autocorrelation truly extended out beyond the spatial extent of our data or that kriging using ArcGIS default parameters was not necessarily providing accurate estimates of spatial autocorrelation. Kriging probability maps in general identified the same areas of high and low probability of weed severity that the Gi* method identified (kriging probability data not shown, Gi* results presented below in the section on ''Hot Spot Localization''). One methodological concern with kriging is the possible impact of violation of the stationarity assumption on results (Isaaks and Srivastava 1989). Kriging options in ArcGIS include detrending for removal of up to third order trends, with the polynomial surface added back into the final prediction map. We explored the effects of first and second order detrending of data for roughstalk bluegrass, annual bluegrass, and German velvetgrass, species showing strong concentrations in particular regions of our study area, and also for other species with more scattered occurrence. Use of detrending had virtually no impact on the prediction maps for any of the weeds. Detrending did generate a few relatively minor differences in kriging probability maps for annual and roughstalk bluegrass, species with strong concentrations near the center of the study area and diminished severity near some of the edges, particularly the northeast. These minor differences generally occurred on very small scales, seldom shifting boundaries for particular probability levels by more than 300 m. A likely cause for the absence of benefits from detrending (or the absence of problems with stationarity) can be found in the statement by Isaaks and Srivastava (1989) that ''the stationarity assumption applies not to the entire data set but only to the search neighborhood'' used in kriging around each point. As we show below in the section on ''Distance for Peak and Maximum Range of Significance of Spatial Autocorrelation and High/Low Clustering,'' the average distance at which spatial autocorrelation peaked was 13.5 km for Moran's I and 17.7 km for General G, values small enough compared to the entire study area that the stationarity assumption would be relatively easily satisfied in the local search radius neighborhood. Rather than attempting to optimize parameter settings and model selection for kriging, we chose to use Moran's I and Getis-Ord General G to measure spatial autocorrelation in our weeds, and hot-spot analysis to develop maps for release to the general public.

Other potential concerns in spatial data analysis include boundary effects, scaling issues, the modifiable areal unit problem, and clustering of sample locations (Schabenberger and Gotway 2005; Unwin 1996). The underlying theme in all of these concerns is the possibility that the statistical results which are obtained might be sensitive to the scales at which data are aggregated and arbitrary boundaries used in that aggregation. The general approach we took to minimize such problems was to avoid aggregating data by political boundaries and land ownership patterns, instead using distances between field centroids in all our spatial analyses. The OSCS field inspection process itself aggregated data at the individual field level, and we have no way of knowing what, if any, problems such within-field aggregation might have created. Delineation of weed patches within fields might be a useful approach in further research to determine whether some of the weed species truly cluster most strongly at smaller scales than the ones we could measure between fields. The next level of concern on scaling and boundary issues was whether certain distances between field centroids were unusually common (such as multiples of 0.8 km between square fields 65 ha in size laid out on a grid pattern) and thus able to distort measurement of spatial autocorrelation. Two factors worked to limit this concern. First, grass seed fields in Linn County, OR, occurred in a wide range of shapes and sizes (mean size 18.4 ha, standard deviation 17.4 ha), reducing the likelihood that certain particular distances between field centroids were overly common. Second, values obtained for ranges at which spatial autocorrelation peaked (see next section below) for most weeds greatly exceeded low integer multiples of the 0.4 km distance between adjacent square 16.2 ha fields, the most common field size. The final scaling issue was whether results near the outer spatial boundary of the data were erratic because points near a boundary might have relatively few neighbors compared to points further into the interior. If the distance at which spatial autocorrelation peaked had turned out to be on the order of the distance between fields and their nearest neighbors, then points near the outer boundary would indeed have had relatively small numbers of neighbors compared to points further in, and hence more erratic measurements of spatial statistics. Because the range at which spatial autocorrelation peaked for most weeds was much larger than typical distance between nearest neighboring fields, even points on the very edge of our study area possessed a large number of neighbors for use in calculations of spatial autocorrelation. One additional concern in spatial statistics is that the sample points themselves might form a nonrandom pattern and cluster most strongly at certain scales. Even though the Moran's I and Getis-Ord General G statistics actually measure the extent to which values (e.g., weed severity) at points in space cluster more strongly than the points themselves, we also conducted Ripley's K-function analysis to directly measure clustering of the fields. Ripley's K-function measures clustering over a range of distances, and it indicated that the field centroids possessed moderately strong clustering at small distances, with clustering becoming nonsignificant at all distances beyond 34 km. Ripley's K-function includes a weight field option that can be set to the severity of individual weeds, and doing so increased the strength of clustering in all cases over that for the fields themselves (data not shown). Although Ripley's K-function might serve as an alternative approach to the one we used to measure distance of peak spatial autocorrelation, it was not available in the earlier version of ArcGIS with which we conducted most of our analyses.

Even without extensive efforts to optimize parameters, kriging of maximum weed severity over the 10-yr period showed that at least 35 of the 43 weeds were spatially autocorrelated to some degree. Kriging also identified German velvetgrass as being the species for which spatial autocorrelation was the strongest. The simplest agronomic interpretation of strong spatial autocorrelation is that a weed is not just randomly present across the landscape, but rather is favored in certain geographic areas and less likely to do well in others. Possible causes for such an effect are numerous, and although our exploratory analysis using kriging neither confirmed nor denied any of them, the list must logically include soil type acting as a surrogate for soil chemical and physical properties, crop species grown, crop management practices (including stand establishment procedures, crop rotation options, stand age, postharvest residue management [baling, field burning, full straw load chop], and available weed control techniques), and stochastic events in landownership history and weed species introductions into fields. Evidence for or against the role of any of these particular factors in creating the current patterns of weed occurrence and severity, and the spatial autocorrelation of those occurrences and severity, are presented in sections below as such evidence is uncovered in more detailed analyses.

Moran's I Spatial Autocorrelation of Maximum Weed Severity within Fields over the 10-yr Period. Puzzling differences occurred when Moran's I spatial autocorrelation of 43 weeds using default settings in ArcGIS (simple inverse distance weighting) were conducted on the maximum severity observed over the 10-yr period within fields and on the observed severity in fields within individual years. Specifically, spatial autocorrelation was more frequently significant within individual years than using the maximum severity over the 10-yr period. Spatial autocorrelation for the 10-yr maximum severity was also more frequently significant using the fixed-distance neighborhood method over a wide range of critical neighborhood distances than when using simple inverse distance weighting. We therefore examined the distance matrix for our 2,785 fields, and discovered that of the 3,876,720 pairs of nonidentical fields, centroids were less than 1 m apart for three pairs, less than 10 m for 37 pairs, less than 30 m for 77 pairs, less than 100 m for 223 pairs, less than 200 m for 628 pairs, and less than 400 m for 2,503 pairs. In contrast to these unusually close fields, the average distance between fields was 28 km. Removal of pairs of fields from the inverse distance matrix whose distances were less than 30 m dramatically changed the Moran's I spatial autocorrelation for 10-yr maximum severity, with all 43 weeds showing significant spatial autocorrelation, in contrast to only four weeds (field bindweed, German velvetgrass, annual bluegrass, and Italian ryegrass, excluding cases grown as crop) when all pairs of points were included. These unusually close distances between field centroids generally represented cases where field boundaries had been changed from one certified crop to the next, and their existence complicated efforts to measure spatial autocorrelation consistently. Rather than simply excluding from analysis pairs of points closer than some arbitrarily designated distance, we explored the impact of adding a wide range of distance offset values (results averaged over all 43 weeds for offsets ranging from 0.3 to 12,875 m are shown in Figure 1) to distance measurements prior to taking inverses in inverse distance weighting matrices. The approach we took of adding relatively small spatial offsets to distances between fields was in line with suggestions by Mitchell (2005) who warned ArcGIS users about problems that unusually close points could cause in the calculation of spatial autocorrelation. Spatial autocorrelation was significant for all 43 weeds using distance offset values ranging from 12.5 to 12,875 m, and an offset of 6 m was sufficient to achieve significance for 41 of 43 weeds (data not shown). Peak of the cubic polynomial fit to Moran's I spatial autocorrelation averaged over the 43 weeds occurred at 2,287 m, whereas spatial autocorrelation greater than or equal to 90% of this peak occurred over a wide range from 330 to 12,567 m (Figure 1). Similar analyses using median rather than mean Z-scores for Moran's I spatial autocorrelation indicated that optimal spatial offsets ranged from 201 to 3,219 m. These results implied that there was a broad range in acceptable spatial offsets capable of correcting the simple inverse distance weighting analysis artifacts generated by the small number of overlapping fields in the 10-yr record. There was little reason to worry about exactly which value was selected for the spatial offset as long as it was large enough to remove the dominance of the few very closely spaced centroids and not so large as to dilute out real effects among the majority of fields. In calculations of spatial autocorrelation of weed severity scores within individual years, no meaningful differences existed between analyses conducted using modestly-sized spatial offsets (e.g., 402 m) and the ArcGIS inverse distance weighting default of no offset (data not shown). Because kriging groups points into a somewhat arbitrary number of bins defined by integer multiples of a common lag distance measured out from each individual point (Isaaks and Srivastava 1989), the few closely separated

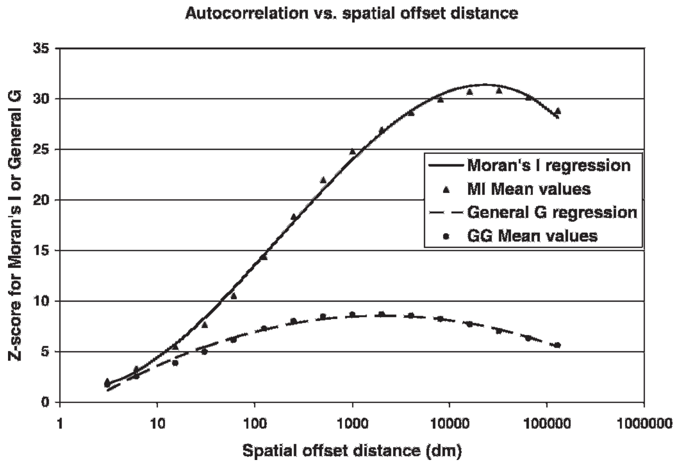


Figure 1. Moran's I spatial autocorrelation and Getis-Ord General G high/low clustering of weed severity averaged over 43 weed species vs. offsets in decimeters added to Euclidean distance between field centroids. Moran's I = 1.3835 − 1.7131 · log(offset) + 5.5249 · log(offset)^2 − 0.8149 · log(offset)^3, R^2 = 0.754. General G = −1.6401 + 6.1687 · log(offset) − 0.9335 · log(offset)^2, R^2 = 0.843. R^2 based on general linear model including main effects of weed species and polynomial logarithmic offset distances.

centroids in the 10-yr maximum severity data had no undesirable impact on calculations of the empirical semivariogram central to the kriging process. In kriging our data, we typically used 50 to 200 bins with lag sizes from 100 to 400 m, creating bins usually containing at least 10 and often as many as 100 points apiece. Unlike the inverse distance weighting procedure being used in Moran's I calculations, kriging would assign equal weights to all points within a single bin, and hence a few extremely closely spaced points could not dominate the calculations. It is interesting to note that the size of the spatial offset we added to the inverse distance weighting matrices to correct the artifact caused by the few overlapping fields was similar to the typical lag size used in kriging the data.

Using a 402 m distance offset in creation of the weighting matrix, the nine weeds with strongest spatial autocorrelation for their 10-yr maximum severity, arranged in decreasing order of strength, were German velvetgrass, field bindweed, roughstalk bluegrass, annual bluegrass, orchardgrass, common velvetgrass, Italian ryegrass, *Agrostis* spp. (creeping bentgrass [*Agrostis stolonifera* L. AGSST] and Colonial bentgrass [*Agrostis tenuis* Sibth. AGSTE]), and perennial ryegrass (Table 1). These nine species were also the only ones with Z-scores for spatial autocorrelation in excess of the mean for all species. With exception of Kentucky bluegrass and roughstalk bluegrass, spatial autocorrelation for the seven weeds also grown as crops was stronger when fields growing those crops were included in the analyses than when they were excluded. For orchardgrass, *Agrostis* spp., and perennial ryegrass, spatial autocorrelation was stronger than the mean over all weeds only when fields in which these species were grown as crops were included.

Statistically significant spatial autocorrelation was found to exist in maximum severity within fields over the 10-yr period for all 43 weeds using Moran's I. Large differences existed among weed species in the strength of this spatial autocorrelation, and the list of weeds with the strongest spatial autocorrelation includes most of the weeds viewed as serious problems by the grass seed industry. This overlap is unlikely to be a random coincidence, and instead implies that weeds such as German velvetgrass, field bindweed, roughstalk bluegrass, annual bluegrass, Italian ryegrass, and *Agrostis* spp. are to some degree heterogeneous rather than ubiquitous problems in grass seed production. Behaviors of Italian ryegrass represent several ways in which this can occur. First, this species is widely grown as a crop, and fields in which it was recently grown are prime candidates for problems with it in other following crops. Second, it is much more likely to be a problem in first-year, fall-planted stands of other grass seed crops as opposed to older stands. Because the crops themselves vary in typical stand life, they also would vary in proportion of that life represented by the establishment year. Problems with roughstalk bluegrass and *Agrostis* spp. typically increase in severity with stand age, and hence could vary with other factors influencing how long individual grass seed stands are kept in production.

Getis-Ord General G High/Low Clustering of Maximum Weed Severity within Fields over the 10-yr Period. Getis-Ord General G high/low clustering analyses were conducted over the same sets of data using the same distance (neighborhood) weighting procedures as had been used for Moran's I spatial autocorrelation. In no cases was General G high/low clustering for maximum severity over the 10-yr period significant for the lower than average weed severity values (Table 2). Only five weeds showed significant high value clustering using the simple inverse distance weighting method. Spatial offsets between pairs of points of 0.3, 0.6, 1.5, 3, 6, 12.5, 25, 50, 101, 201, and 402 m in inverse distance weighting matrices increased significance of high value clustering to 15, 21, 31, 33, 33, 35, 36, 37, 37, 37, and 37 of the 43 cases for 10-yr maximum weed severity (data not shown). Peak of the quadratic polynomial fit to General G high/low clustering occurred at 201 m, whereas high/low clustering greater than or equal to 90% of this peak occurred over a range from 22 to 1825 m (Figure 1).

In general, Z-scores for Getis-Ord General G high/low clustering were substantially lower than corresponding Z-scores for Moran's I spatial autocorrelation, with median Z-scores for General G being smaller by a factor of 3.07-fold. In addition to the six fewer cases of significance at optimum spatial offset, a slightly different group of weeds possessed higher than average Z-scores for General G high/low clustering than for Moran's I spatial autocorrelation. The 14 weeds with above-average high value clustering, arranged in decreasing order of strength, were German velvetgrass, field bindweed, *Amaranthus* spp. (Powell amaranth [*Amaranthus powellii* S. Wats. AMAPO] and redroot pigweed [*Amaranthus retroflexus* L. AMARE]), Kentucky bluegrass, roughstalk bluegrass, annual bluegrass, quackgrass [*Elytrigia repens* (L.) Nevski AGRRE], *Agrostis* spp., western wildcucumber, common velvetgrass, rattail fescue, sharppoint fluvellin [*Kickxia elatine* (L.) Dumort KICEL], perennial ryegrass, and orchardgrass. For the seven weeds also grown as crops, General G high value clustering showed more variable responses to inclusion or exclusion of fields growing those crops than occurred with Moran's I spatial autocorrelation. Similar to Moran's I results, high value clustering was stronger when fields growing those crops were included in the analyses rather than excluded for *Agrostis* spp. and orchardgrass. In contrast to the Moran's I analyses, high value clustering was stronger when fields growing those crops were excluded from

Table 1. Moran's I spatial autocorrelation for severity of common grass seed weeds, Linn County, Oregon, by 10-yr maximum and by year, 1994 to 2003.

	Z-score for 10-yr maximum or single year severity index[a]										
Weed species	10-yr maximum severity	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
AGRRE	**28.16**	**4.02**	**11.17**	**6.39**	**4.92**	**2.90**	**3.33**	**8.67**	**8.76**	**4.88**	**17.96**
AGSST & AGSTE[b]	**42.46**	**24.73**	**23.10**	**30.42**	**28.53**	**28.61**	**35.05**	**28.40**	**18.31**	**19.36**	**18.64**
AGSST & AGSTE[c]	**18.81**	0.84	**4.47**	**6.35**	**5.36**	**3.28**	**3.27**	**3.28**	**6.57**	**6.34**	**5.48**
AMAPO & AMARE	**21.84**	**9.51**	**3.53**	0.69	**8.12**	**4.18**	**3.52**	1.26	1.90	1.73	**9.90**
ANTCO	**13.33**	**7.43**	0.43	**5.74**	0.81	**6.66**	**6.30**	**3.30**	**3.38**	1.06	**2.94**
AVESA & AVEFA	**19.65**	**4.74**	**2.90**	**9.01**	**3.82**	**11.08**	**4.77**	**9.21**	**7.57**	**3.79**	**3.70**
Bromus spp.	**15.13**	**3.63**	**9.04**	**9.83**	**5.55**	**7.52**	**8.87**	**8.54**	**3.66**	**2.47**	**3.93**
CAPBP	**7.66**	−0.11	1.10	**5.61**	0.77	−0.50	**4.06**	0.45	**3.95**	1.46	−0.30
CIRAR	**19.46**	**11.95**	**8.20**	**9.99**	**6.15**	**9.66**	**6.83**	**6.31**	**10.94**	**7.10**	**2.73**
CONAR	**92.96**	**12.59**	**28.79**	**20.00**	**37.50**	**38.14**	**35.20**	**43.42**	**31.90**	**31.57**	**19.87**
DACGL[b]	**46.15**	**44.38**	**54.47**	**48.86**	**56.10**	**66.17**	**41.65**	**40.47**	**42.94**	**44.22**	**41.05**
DACGL[c]	**25.35**	**8.86**	**19.52**	**15.51**	**5.56**	**6.77**	**5.97**	**7.19**	**11.22**	**13.92**	**16.21**
DAUCA	**11.11**	**2.91**	1.05	0.80	**2.02**	**4.78**	**2.45**	1.52	**4.37**	**3.83**	**4.26**
ECNOR	**27.43**	**8.00**	**20.99**	**19.14**	**13.33**	**10.70**	**9.99**	**10.74**	**13.26**	**12.89**	**7.46**
EQUAR	**5.57**	0.00	−0.04	**3.45**	**4.62**	**3.49**	**3.06**	−0.97	0.04	0.88	1.48
FESAR[b]	**21.99**	**21.60**	**17.47**	**13.14**	**16.86**	**19.04**	**22.84**	**24.37**	**24.14**	**17.93**	**17.59**
FESAR[c]	**15.21**	**10.34**	**6.52**	**4.18**	**3.09**	1.87	**5.18**	**6.03**	**4.37**	1.00	**2.62**
GALAP	**7.68**	**2.03**	1.49	1.78	**3.91**	−0.01	0.57	0.67	**6.49**	0.02	**2.19**
HOLLA	**45.51**	**11.36**	**13.65**	**6.55**	**10.92**	**13.24**	**6.39**	**10.47**	**16.62**	**18.69**	**13.54**
HOLMO	**149.27**	**45.62**	**62.57**	**109.42**	**49.74**	**42.50**	**57.71**	**37.17**	**19.16**	**13.63**	**12.79**
HRYRA	**8.78**	−0.20	**3.26**	1.70	**2.41**	1.87	−0.12	1.18	**6.24**	**7.92**	−0.47
KICEL	**15.78**	0.64	0.00	**8.95**	**2.27**	−0.53	0.82	**3.07**	**8.09**	**5.75**	**6.28**
LACSE	**6.21**	**4.61**	−0.58	0.93	0.75	**3.21**	−1.52	**5.69**	**4.16**	−0.04	**3.42**
LOLMU[b]	**43.70**	**17.93**	**12.50**	**6.34**	**19.59**	**17.03**	**10.66**	**16.18**	**17.27**	**10.03**	**14.06**
LOLMU[c]	**41.16**	**17.93**	**13.55**	**8.37**	**14.51**	**19.07**	**10.87**	**9.32**	**10.20**	**3.56**	**8.46**
LOLPE[b]	**33.72**	**26.80**	**23.04**	**20.38**	**18.19**	**23.17**	**21.00**	**22.19**	**19.70**	**17.41**	**20.36**
LOLPE[c]	**12.82**	**5.87**	**8.75**	**3.66**	**4.85**	**4.08**	**6.69**	**4.13**	1.52	**3.37**	1.53
Lowland cudweed	**17.48**	**2.18**	**3.03**	**8.13**	**3.51**	−0.48	**2.58**	**7.77**	0.83	**5.61**	0.90
MATMT	**8.34**	1.37	−0.65	0.62	**2.77**	0.51	1.39	1.60	1.21	**4.03**	**4.57**
POAAN	**79.73**	**13.88**	**20.65**	**33.49**	**19.75**	**27.82**	**23.58**	**21.61**	**15.71**	**17.43**	**25.65**
POAPR[b]	**27.71**	**31.00**	**18.24**	**5.45**	**2.41**	**8.58**	**12.76**	**3.98**	**9.91**	**14.71**	**13.97**
POAPR[c]	**28.55**	−1.05	**9.45**	**2.07**	**4.83**	**4.79**	**16.17**	**5.16**	**10.33**	**13.33**	**12.53**
POATR[b]	**76.43**	**15.28**	**26.65**	**22.85**	**16.16**	**33.29**	**23.54**	**28.90**	**21.13**	**7.59**	**23.10**
POATR[c]	**81.82**	**17.16**	**29.15**	**22.85**	**16.16**	**33.29**	**23.54**	**28.90**	**21.13**	**9.60**	**25.50**
POLPE	**13.03**	**7.58**	**2.05**	**4.06**	**5.07**	**5.09**	**8.04**	**8.82**	**2.08**	**4.73**	**3.67**
RUBDI	**10.61**	0.00	0.00	0.00	**4.32**	1.18	**5.15**	**8.55**	0.06	**4.48**	**3.90**
RUMOB & RUMCR	**7.37**	**5.08**	0.47	**3.54**	**3.87**	0.04	**1.99**	1.83	**4.17**	**2.92**	0.66
SENVU	**15.44**	**3.65**	1.01	**8.71**	**2.89**	**2.83**	1.52	**9.82**	**20.96**	**3.50**	0.71
SINAR	**11.61**	0.15	0.45	**7.05**	**7.45**	**2.03**	1.19	1.11	−0.69	−0.20	−0.62
SONAR	**19.46**	**8.66**	1.35	1.35	**2.35**	**5.62**	**5.06**	**11.28**	**4.94**	**3.47**	**4.93**
TYPAR	**5.08**	1.43	1.62	**2.13**	**4.56**	**3.41**	**3.70**	−0.22	1.65	−0.14	1.10
VLPMY	**20.20**	**7.90**	0.51	**4.56**	**8.03**	**5.83**	1.20	**5.19**	**5.78**	1.95	**8.75**
Wheat	**11.25**	**5.19**	**7.40**	**4.26**	**2.08**	0.84	1.25	1.89	−0.11	**3.18**	**2.12**
Mean Z-score	**28.63**	**9.94**	**10.98**	**11.82**	**10.15**	**11.22**	**10.42**	**10.66**	**9.90**	**8.15**	**9.05**
Median Z-score	**19.46**	**7.43**	**6.52**	**6.35**	**4.92**	**5.09**	**5.18**	**7.19**	**6.57**	**4.73**	**4.93**
No. cases significant	43	33	28	35	40	33	34	32	34	33	34

[a] Z-scores with absolute values in excess of 1.96, 2.575, and 3.27 are significant at the $P \leq 0.05$, 0.01, and 0.001 levels, respectively. Values significant at $P \leq 0.05$ are denoted in **bold** type. Severity index values of 0, 0.75, 1.75, 2.75, and 3.75 denote weed species presence characterized as *absent*, *trace*, *many*, *excessive*, or grown as a previous crop. Distance weight matrix for Moran's I spatial autocorrelation was the reciprocal of the observed distance between field polygon centers plus 402 m.

[b] Including cases in which weed was grown as the crop with assigned severity index of 3.75.

[c] Excluding cases in which weed was present only when grown as the crop.

the analyses for Italian ryegrass and perennial ryegrass. High-value clustering was nonsignificant for tall fescue (*Festuca arundinacea* Schreb. FESAR) with or without inclusion of crop cases. As with Moran's I spatial autocorrelation, Getis-Ord General G high value clustering for Kentucky bluegrass and roughstalk bluegrass tended not to be affected by whether or not the few fields in which they were grown as crops in western Oregon were included. We chose a spatial offset of 402 m for all further analyses because that value did the best job of simultaneously maximizing both Moran's I spatial autocorrelation and Getis-Ord General G high/low clustering, although results would have been nearly identical using any offset in a range from 201 to 1,609 m. An alternate perspective on use of the spatial offset is to simply view it as a means of representing possible uncertainty in location of weeds within individual fields in the calculation of distances between fields, because the average field size of 18.4 ha would correspond to an average field width of 429 m. Further confirmation of the validity of our use of spatial offsets comes from comparison of average Z-scores for Moran's I and Getis-Ord General G at peak distance in the fixed distance weighting method (average Z-scores = 30 and 10 in Table 3) with maxima of the polynomial curves of Z-score vs. spatial offset distance in the inverse distance weighting method (Z-score maxima = 31 and 9 in Figure 1).

Similarities and differences between Moran's I spatial autocorrelation and Getis-Ord General G high/low clustering of maximum weed severity in the 10-yr period provide several further insights into agronomic factors influencing the behavior of weeds. In no case was General G significant for

Table 2. Getis-Ord General G high/low clustering for severity of common grass seed weeds, Linn County, OR, by 10-yr maximum and by year, 1994 to 2003.

	Z-score for 10-yr maximum or single year severity index[a]										
Weed species	10-yr maximum severity	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
AGRRE	**13.50**	**3.52**	**8.52**	**4.45**	**4.27**	**2.99**	**3.09**	**4.96**	**7.79**	**4.65**	**13.31**
AGSST & AGSTE[b]	**12.30**	**11.24**	**8.91**	**11.86**	**14.96**	**14.10**	**19.08**	**14.41**	**8.60**	**10.01**	**11.82**
AGSST & AGSTE[c]	−0.16	0.77	−0.72	**−2.24**	1.35	−0.25	−0.34	0.01	**3.52**	**3.11**	**4.01**
AMAPO & AMARE	**15.72**	**8.49**	**2.88**	0.58	**7.15**	**4.88**	**3.78**	1.46	1.92	**2.45**	**10.83**
ANTCO	**6.38**	**4.15**	0.59	**2.73**	1.23	**5.73**	**4.25**	**2.00**	1.90	0.27	1.80
AVESA & AVEFA	**6.07**	**3.17**	0.32	**5.50**	**1.99**	**8.18**	**2.45**	**3.67**	**5.38**	**2.83**	**2.59**
Bromus spp.	0.52	1.20	**2.53**	**6.25**	**2.69**	**3.90**	**2.48**	1.10	1.65	0.93	0.43
CAPBP	**3.59**	−0.54	0.97	**3.89**	−0.14	0.06	**2.93**	−0.10	**3.04**	1.21	0.10
CIRAR	**4.76**	**5.01**	**5.63**	**4.76**	**4.82**	**5.39**	**2.61**	**2.18**	**3.65**	**2.39**	1.78
CONAR	**32.69**	**9.64**	**19.78**	**14.34**	**27.10**	**29.18**	**26.58**	**24.81**	**17.86**	**19.67**	**12.71**
DACGL[b]	**8.76**	**20.64**	**24.00**	**22.36**	**26.47**	**27.84**	**17.03**	**12.84**	**13.78**	**16.03**	**14.53**
DACGL[c]	**5.08**	**5.96**	**11.36**	**9.13**	**2.66**	**6.31**	**5.02**	0.74	**2.84**	**6.89**	**7.18**
DAUCA	**3.46**	**3.49**	0.37	−0.34	**2.31**	**5.14**	1.21	0.64	0.76	0.36	**1.96**
ECNOR	**11.13**	**5.96**	**13.63**	**12.51**	**10.10**	**7.60**	**7.68**	**6.34**	**8.83**	**9.19**	**5.88**
EQUAR	**3.04**	0.00	−0.04	**2.48**	**4.40**	**2.57**	**3.37**	−0.38	1.03	0.44	0.56
FESAR[b]	−0.24	**6.26**	**2.75**	1.86	**2.10**	**4.41**	**3.64**	**3.18**	**4.14**	**2.24**	−0.50
FESAR[c]	1.48	**4.89**	1.77	1.27	−0.15	−0.67	1.91	0.86	1.73	−0.24	1.57
GALAP	**5.71**	1.07	**2.08**	1.60	**2.72**	−0.07	1.21	0.41	**6.17**	0.40	1.93
HOLLA	**10.53**	**7.22**	**6.29**	**2.65**	**3.48**	**5.85**	**5.14**	**3.24**	**7.35**	**9.57**	**9.55**
HOLMO	**50.66**	**26.29**	**36.81**	**54.55**	**31.56**	**27.45**	**34.02**	**24.28**	**12.81**	**8.70**	**10.30**
HRYRA	**1.99**	−0.13	1.28	0.13	1.30	1.89	−0.43	−0.03	**4.52**	**5.26**	−0.01
KICEL	**9.83**	0.64	0.00	**8.17**	**2.59**	−0.12	1.34	**2.10**	**6.58**	**4.24**	**4.25**
LACSE	**3.03**	**3.49**	−0.48	−0.09	−0.67	**4.47**	−0.92	**2.63**	**2.30**	0.99	1.56
LOLMU[b]	**3.79**	**8.33**	**4.66**	0.68	**3.93**	**3.26**	0.89	**2.36**	**3.35**	**3.03**	**4.89**
LOLMU[c]	**4.59**	**8.33**	**4.90**	**2.05**	1.18	**4.68**	1.56	−0.51	**2.34**	0.69	**2.98**
LOLPE[b]	**7.36**	**10.61**	**8.06**	**7.32**	**3.78**	**4.68**	**4.70**	**5.57**	**6.69**	**6.68**	**8.14**
LOLPE[c]	**9.42**	**5.56**	**8.40**	**2.93**	**5.40**	**3.46**	**5.77**	**2.84**	1.58	**3.13**	**2.05**
Lowland cudweed	**5.70**	**2.46**	**3.71**	**7.06**	**2.59**	−0.58	1.09	**4.24**	0.15	1.68	0.06
MATMT	**5.18**	1.37	−0.61	−0.60	1.86	0.51	1.09	1.19	0.90	**3.86**	**4.01**
POAAN	**13.61**	**10.97**	**11.62**	**16.84**	**8.95**	**10.46**	**4.93**	**5.12**	**5.96**	**7.23**	**8.51**
POAPR[b]	**15.48**	**29.87**	**15.79**	**4.08**	**2.59**	**8.20**	**8.58**	**2.12**	**6.94**	**11.86**	**10.85**
POAPR[c]	**14.67**	−1.05	**9.14**	1.71	**4.92**	**4.68**	**10.89**	**2.82**	**7.19**	**10.54**	**9.42**
POATR[b]	**13.55**	**7.81**	**12.37**	**10.16**	**5.35**	**13.55**	**6.21**	**5.66**	**8.92**	**4.25**	**10.15**
POATR[c]	**14.36**	**8.83**	**13.44**	**10.16**	**5.35**	**13.55**	**6.21**	**5.66**	**8.92**	**5.08**	**11.25**
POLPE	**4.10**	**5.64**	0.87	1.41	**2.07**	**4.61**	**7.28**	**6.01**	1.72	**3.09**	1.33
RUBDI	**7.26**	0.00	0.00	0.00	**4.87**	0.75	**5.51**	**8.34**	0.07	**3.87**	**2.21**
RUMOB & RUMCR	0.28	**3.87**	0.41	0.68	1.77	0.08	0.99	−0.87	**1.97**	0.75	0.18
SENVU	**6.71**	**2.27**	1.02	**5.18**	**2.24**	**4.12**	0.92	**5.56**	**10.64**	**1.98**	0.22
SINAR	**5.83**	−0.23	0.02	**4.99**	**4.85**	**2.88**	0.88	0.03	0.42	0.35	−1.07
SONAR	**7.99**	**8.04**	**2.54**	1.40	1.79	**5.23**	**5.04**	**7.33**	**2.35**	0.95	**2.22**
TYPAR	1.49	1.32	0.76	1.82	**3.99**	1.88	**2.04**	−1.40	**1.97**	−0.57	1.08
VLPMY	**10.31**	**5.54**	0.44	**2.78**	**7.18**	**4.94**	1.23	**4.81**	**4.84**	1.47	**9.14**
Wheat	**6.34**	**4.94**	**6.97**	**2.63**	1.32	0.59	0.20	1.66	0.10	**3.00**	1.83
Mean Z-score	**8.55**	**5.97**	**5.90**	**5.85**	**5.36**	**6.01**	**5.19**	**4.18**	**4.77**	**4.29**	**4.83**
Median Z-score	**6.34**	**4.94**	**2.75**	**2.78**	**2.72**	**4.61**	**3.09**	**2.63**	**3.52**	**3.03**	**2.59**
No. cases significant high value clustering	37	31	25	28	32	31	27	27	30	28	26

[a] Z-scores with absolute values in excess of 1.96, 2.575, and 3.27 are significant at the $P \leq 0.05$, 0.01, and 0.001 levels, respectively. Values significant at $P \leq 0.05$ are denoted in **bold** type. Severity index values of 0, 0.75, 1.75, 2.75, and 3.75 denote weed species presence characterized as *absent*, *trace*, *many*, *excessive*, or grown as a previous crop. Distance weight matrix for Getis-Ord General G high/low clustering was the reciprocal of the observed distance between field polygon centers plus 402 m.

[b] Including cases in which weed was grown as the crop with assigned severity index of 3.75.

[c] Excluding cases in which weed was present only when grown as the crop.

low value clustering, although on average General G significance values were substantially lower than Moran's I. In other words, spatial autocorrelation detected by Moran's I was primarily, though not entirely, due to clustering of fields where weeds were present rather than where they were absent. This means that we can discount clustering of management practices that were unusually effective in controlling weeds as being the major underlying cause for spatial autocorrelation of most weeds. If clustering of any management practices was a cause for spatial autocorrelation of weeds, it was much more likely to have been clustering of ineffective practices. Such practices are all too easily visualized, and range from grower decisions to apply herbicides to all of his or her fields at rates either too low for optimal weed control in an effort to save money or too high for optimal crop tolerance in misguided attempts to kill the last few percent of some particular weed, efforts that often open up space in the stand for future invasion by additional weeds. Because fields owned or operated by a single grower are likely to be clustered due to economic and logistical factors, any nonoptimal management practices used by that grower will also be clustered. Italian ryegrass represented an interesting exception to the concept that ineffective management practices generally played greater roles than highly effective ones in causing weeds to cluster. Italian ryegrass was the seventh most strongly clustered weed as measured by Moran's I spatial autocorrelation, but it ranked near the bottom (30th and 32nd excluding and including cases in which it was grown as a crop) using General G high/low clustering. This disparity in ranking between Moran's I and General G must mean that low values of severity were clustering in almost as many cases as high values. In other words, this weed was nearly universally present in

Table 3. Distance of peak clustering and maximum range of significance for Moran's I spatial autocorrelation and Getis-Ord General G high/low clustering for 10-yr maximum observed severity of common grass seed weeds, Linn County, OR, using fixed distance weighting method.

	Moran's I spatial autocorrelation			Getis-Ord General G high/low clustering		
Weed species	Distance for peak autocorrelation	Z-score at peak distance[a]	Maximum range of significance	Distance for peak clustering	Z-score at peak distance[a]	Maximum range of significance
	km	Z-value	km	km	Z-value	km
AGRRE	15	**29.31**	53	14	**8.81**	60
AGSST & AGSTE[b]	2	**33.96**	39	1	**22.92**	16
AGSST & AGSTE[c]	5	**17.90**	19	1	**3.10**	3
AMAPO & AMARE	5	**21.90**	29	5	**17.33**	27
ANTCO	59	**5.79**	71	48	**3.26**	59
AVESA & AVEFA	4	**16.53**	40	40	**5.03**	63
Bromus spp.	2	**13.54**	40	46	**5.02**	67
CAPBP	12	**5.85**	22	2	**5.81**	5
CIRAR	4	**18.12**	52	3	**6.22**	7
CONAR	6	**86.96**	32	3	**34.63**	42
DACGL[b]	5	**38.28**	54	2	**11.16**	17
DACGL[c]	6	**26.13**	46	46	**5.98**	67
DAUCA	20	**11.89**	36	31	**5.86**	61
ECNOR	2	**27.15**	12	1	**17.30**	10
EQUAR	11	**6.78**	25	12	**3.35**	16
FESAR[b]	9	**17.90**	22	17	**3.39**	22
FESAR[c]	14	**14.26**	29	39	**4.10**	62
GALAP	14	**5.31**	23	29	**3.78**	44
HOLLA	34	**59.29**	75	35	**5.38**	60
HOLMO	13	**181.48**	76	8	**60.74**	35
HRYRA	31	**8.72**	73	32	**2.17**	47
KICEL	8	**19.60**	17	5	**10.83**	24
LACSE	19	**9.58**	38	26	**4.50**	65
LOLMU[b]	18	**40.90**	42	32	**9.43**	67
LOLMU[c]	14	**37.97**	37	36	**10.16**	68
LOLPE[b]	13	**32.79**	47	35	**7.01**	64
LOLPE[c]	2	**13.75**	15	2	**13.00**	15
Lowland cudweed	17	**20.20**	45	17	**7.74**	65
MATMT	17	**7.82**	33	2	**5.72**	18
POAAN	14	**97.29**	45	14	**15.26**	73
POAPR[b]	23	**26.09**	63	10	**10.03**	36
POAPR[c]	7	**29.26**	52	6	**15.13**	65
POATR[b]	14	**97.60**	36	14	**15.19**	70
POATR[c]	14	**102.74**	36	14	**15.97**	70
POLPE	11	**13.89**	38	14	**6.33**	30
RUBDI	33	**9.17**	59	33	**2.75**	43
RUMOB & RUMCR	10	**6.95**	27	19	**2.27**	22
SENVU	17	**12.84**	32	23	**3.81**	35
SINAR	8	**10.83**	33	2	**6.48**	10
SONAR	13	**18.08**	54	19	**7.65**	68
TYPAR	11	**3.08**	14	17	**1.98**	17
VLPMY	19	**19.65**	74	4	**12.95**	21
Wheat	7	**10.35**	28	2	**4.96**	14
Mean	13.53	**29.94**	40.30	17.70	**9.87**	40.70
Median	13	**18.08**	38	14	**6.33**	42
No. cases significant		43			43	

[a] Z-scores with absolute values in excess of 1.96, 2.575, and 3.27 are significant at the P ≤ 0.05, 0.01, and 0.001 levels, respectively. Values significant at P ≤ 0.05 are denoted in **bold** type. Severity index values of 0, 0.75, 1.75, 2.75, and 3.75 denote weed species presence characterized as *absence*, *trace*, *many*, *excessive*, or grown as a previous crop. Distance for peak autocorrelation and high/low clustering and maximum range of significance were identified by iterative testing using the fixed distance band method with 1 km changes between runs until peaks and maximum ranges were found.

[b] Including cases in which weed was grown as the crop with assigned severity index of 3.75.

[c] Excluding cases in which weed was present only when grown as the crop.

Linn County grass seed fields, and clustering of management practices that effectively controlled it was almost as important as clustering of ineffective practices in generating the large value for Moran's I spatial autocorrelation.

Moran's I Spatial Autocorrelation of Weed Severity over Time. Within individual years from 1994 to 2003, the number of weeds for which Moran's I spatial autocorrelation of severity was significant ranged from a low of 28 cases in 1995 to a high of 40 cases in 1997 (Table 1). Weeds with the strongest spatial autocorrelation for 10-yr maximum severity were those most likely to have significant spatial autocorrelation within individual years. Spatial autocorrelation was significant in all 10 individual yr for German velvetgrass, field bindweed, roughstalk bluegrass, annual bluegrass, orchardgrass, common velvetgrass, Italian ryegrass, *Agrostis* spp. (when crop cases were included), perennial ryegrass (when crop cases were included), quackgrass, *Avena* spp. (oat [*Avena sativa* L. AVESA] and wild oat [*Avena fatua* L. AVEFA]), *Bromus* spp. (downy brome [*Bromus tectorum* L. BROTE], California brome, and other unidentified bromes), Canada thistle, western wildcucumber, tall fescue (when crop cases were included), Kentucky bluegrass (when crop cases were included), and ladysthumb (*Polygonum persicaria* L. POLPE). When crop cases were excluded, the number of years in which spatial autocorrelation was significant dropped to nine for *Agrostis* spp. and Kentucky bluegrass, and to eight for tall fescue and perennial ryegrass. Weeds showing the lowest spatial autocorrelation for 10-yr maximum severity tended to be those least likely to have significant spatial autocorrelation within individual years. Spatial autocorrelation was significant in only 3 of 10 yr for shepherd's-purse [*Capsella bursa-pastoris* (L.) Medicus CAPBP], catchweed bedstraw (Galium aparine L. GALAP), pineapple-weed [*Matricaria matricarioides* (Less.) C. L. Porter, MATMT], and wild mustard [*Brassica kaber* (DC.) L. C.Wheeler SINAR], 4 yr for field horsetail (*Equisitum arvense* L. EQUAR), common catsear (*Hypochoeris radicata* L. HRYRA), and reed canarygrass (*Phalaris arundinacea* L. TYPAR), and 5 yr for prickly lettuce and Himalaya blackberry.

Wild carrot is commonly viewed to have increased substantially in severity in western Oregon in recent history (Cole et al. 2006). This weed showed significant spatial autocorrelation in only 1 of the first 3 yr, but was spatially autocorrelated in 3 of the middle 4 yr and all 3 of the final 3 yr. Such a pattern is certainly consistent with a weed doubling in severity and increasing in geographic extent over this time period, although other more elaborate interpretations might be made. Agronomic practices changing over this time period include decreased use of field burning, changes in frequency of fall vs. spring planting, shorter stand life of grass seed fields, reduced rotation with cereals due to low commodity prices, and increased restrictions on use of soil residual herbicides (e.g., triazines). Although any of these changes might have favored the proliferation of wild carrot, we lack sufficient knowledge of production practices on individual fields to apportion blame. No obvious temporal trends were present in spatial autocorrelation averaged over all weed species, a finding consistent with the concept that most of these weeds had long since spread across the landscape and achieved approximate equilibrium with current crop rotation and within-crop weed control practices.

Getis-Ord General G High/Low Clustering of Weed Severity over Time. Within individual years from 1994 to 2003, there were 34 cases in which Z-scores for Getis-Ord General G high/low clustering were numerically less than zero, but low value clustering was statistically significant only once (*Agrostis* spp. excluding crop cases in 1996) (Table 2). General G high/low clustering was exactly zero in five cases, weeds with no nonzero severity observations in those years. General G high value clustering was significant in 284 of the 391 remaining cases. The number of weeds for which Getis-Ord General G high value clustering of severity was significant ranged from a low of 25 cases in 1995 to a high of 32 cases in 1997. Weeds with the strongest General G high value clustering for 10-yr maximum severity were those most likely to have significant high value clustering within individual years. General G high value clustering was significant in all 10 individual yr for German velvetgrass, field bindweed, Kentucky bluegrass (when crop cases were included), quackgrass, roughstalk bluegrass, annual bluegrass, *Agrostis* spp. (when crop cases were included), western wildcucumber, common velvetgrass, orchardgrass (when crop cases were included), and perennial ryegrass (when crop cases were included). When crop cases were excluded, the number of years for which high value clustering was significant dropped to nine for orchardgrass and perennial ryegrass, to eight for Kentucky bluegrass, to six for Italian ryegrass, to three for *Agrostis* spp., and to one for tall fescue. Weeds showing the lowest General G high value clustering for 10-yr maximum severity tended to be those least likely to have significant high value clustering within individual years. High-value clustering was significant in only 2 yr out of 10 for common catsear, pineapple-weed, and *Rumex* spp. (broadleaf dock [*Rumex obtusifolius* L. RUMOB] and curly dock [*Rumex crispus* L. RUMCR]); 3 yr for shepherd's-purse, catchweed bedstraw, wild mustard, and reed canarygrass; 4 yr for wild carrot, field horsetail, prickly lettuce, and wheat; and 5 yr for mayweed chamomile (*Anthemis cotula* L. ANTCO), *Bromus* spp., lowland cudweed (*Gnaphalium palustre* Nutt.), and Himalaya blackberry. No obvious temporal trends were present in General G high value clustering averaged over weed species, a finding consistent with the concept that most of these weeds had reached approximate equilibrium with crop management practices.

Wild carrot underwent an interesting transition over time in comparison of General G high/low clustering vs. Moran's I spatial autocorrelation. In the first 5 yr, both measurements were significant or nonsignificant in the same individual years. In the last 5 yr, however, they essentially decoupled, with General G only achieving borderline significance in a single yr whereas Moran's I only failed to achieve significance one time. Given that the weed was increasing in severity over the entire 10-yr time period, the loss of General G high value clustering in the second half of the decade implies that clustering of management practices or edaphic factors effective in prevention or control of wild carrot had assumed greater importance than the clustering of ineffective practices that favored the weed.

Distance for Peak and Maximum Range of Significance of Spatial Autocorrelation and High/Low Clustering. Knowledge of the distances at which spatial autocorrelation and high/low clustering peak and then fade to nonsignificance would be useful for cluster identification using local Moran's I and Getis-Ord Gi* as well as calculation of semivariograms used in kriging values observed at discrete locations across a landscape (Mitchell 2005). Distance at which Moran's I spatial autocorrelation of 10-yr maximum weed severity peaked ranged from 2 km for *Agrostis* spp. (when crop cases were included), *Bromus* spp., western wildcucumber, and perennial ryegrass (when crop cases were excluded) to 59 km for mayweed chamomile (Table 3). The shortest distance at which significance of spatial autocorrelation was lost was 12 km for western wildcucumber, whereas the greatest distance at which significance was lost was 76 km for German velvetgrass. Distances for peak high/low clustering ranged from 1 km for *Agrostis* spp. and western wildcucumber to 48 km for mayweed chamomile. The shortest distance at which significance of high/low clustering was lost was 3 km for *Agrostis* spp. (when crop cases were excluded), while the greatest distance at which significance was lost was 73 km for annual bluegrass.

Of special interest were distances for peak effect and maximum range of significance for weeds that possessed the strongest spatial autocorrelation and high/low clustering. For

German velvetgrass, spatial autocorrelation peaked at 13 km and extended on out to 76 km, and high value clustering peaked at 8 km and extended on out to 35 km (Table 3). For field bindweed, spatial autocorrelation peaked at 6 km and extended on out to 32 km, whereas high value clustering peaked at 3 km and extended on out to 42 km. For roughstalk bluegrass, spatial autocorrelation peaked at 14 km and extended on out to 36 km, and high value clustering peaked at 14 km and extended on out to 70 km. For annual bluegrass, spatial autocorrelation peaked at 14 km and extended on out to 45 km, whereas high value clustering peaked at 14 km and extended on out to 73 km. Weeds that possessed relatively weak spatial autocorrelation (or high/low clustering) tended to have narrower ranges in their distances from peak significance to maximum range of significance. For spatial autocorrelation, these ranges were 12 to 22 km for shepherd's-purse, 11 to 25 km for field horsetail, 14 to 23 km for catchweed bedstraw, 17 to 33 km for pineapple-weed, 8 to 33 km for wild mustard, 31 to 73 km for common catsear, and 11 to 14 km for reed canarygrass. For high/low clustering, these ranges were 2 to 5 km for shepherd's-purse, 12 to 16 km for field horsetail, 29 to 44 km for catchweed bedstraw, 2 to 18 km for pineapple-weed, 2 to 10 km for wild mustard, 32 to 47 km for common catsear, and 17 to 17 km for reed canarygrass.

Given the areal extent of fields in our GIS of 84 km on a NE–SW axis by 51 km on a NW–SE axis, significant spatial autocorrelation in weeds such as German velvetgrass, common velvetgrass, common catsear, and mayweed chamomile extended out to distances approaching the maximum possible range in our data. Indeed, the range of significant spatial autocorrelation exceeded the 51 km NW–SE axis distance across our study area for 12 of the 43 weeds (Table 3). Although the maximum range of significant spatial autocorrelation averaged 40.3 km by Moran's I and 40.7 km by Getis-Ord General G for the 43 weeds, distance for peak spatial autocorrelation averaged only one-third as much (13.5 km) for Moran's I and 43% as much (17.7 km) for Getis-Ord General G. Because ranges for autocorrelation of weeds from the exploratory kriging analysis (data not shown) had been closer to values for the maximum range of significance than to those for peak autocorrelation distance for fixed distance weighting methods with Moran's I or Getis-Ord General G, the methods we used to determine the range for hot-spot analysis inherently produced higher resolution maps than would have occurred if the substantially larger ranges obtained from exploratory kriging had been used in hot-spot analysis.

Distances for peak Moran's I spatial autocorrelation and Getis-Ord General G high/low clustering were most similar for weeds with high values for General G. Distances for peak autocorrelation or clustering of the two methods agreed to within an average of 1.1 km for the 10 weeds with General G Z-scores in excess of 13.0, whereas differences in peak distance increased to an average of 8.4 km for the 13 weeds with General G between 6.2 and 12.9, and to an average of 12.8 km for the 20 weeds with General G less than 6.0. Among the 10 most strongly clustered weeds, the largest value observed for distance of peak autocorrelation or high/low clustering was 14 km, suggesting that the most convincingly present clusters occurred in sizes less than or equal to 620 km^2. Such sizes correspond to scales at which many farms operate, and farm operators (owners and/or renters) were found to differ significantly in effectiveness of their crop rotations in controlling weeds (data not shown). Distance for peak spatial autocorrelation and high/low clustering presumably represented the combined effects over time of land ownership/rental patterns, choice of crops grown on fields, how those crops were managed, adaptation of weeds to soil types within fields, and stochastic introductions of weeds into fields. Some of the weeds with largest Getis-Ord General G distances for peak clustering (e.g., *Avena* spp., *Bromus* spp., orchardgrass including cases grown as a crop, tall fescue including cases grown as a crop, and Italian ryegrass) were likely associated with past cropping history (cereal crops for *Avena* spp. and *Bromus* spp., the crops themselves for orchardgrass, tall fescue, and Italian ryegrass). Other weeds with large peak clustering distances (e.g., mayweed chamomile, common velvetgrass, and common catsear) might have been more strongly influenced by adaptation to soil type than by specific cropping history. Perennial weeds with very small peak clustering distances (e.g., *Agrostis* spp., Canada thistle, field bindweed, and western wildcucumber) likely represent traditional weed infestations in which patches extend directly across multiple neighboring fields.

Soil Type Effects. A total of 91 soil types occurred in one or more of the 2,785 georeferenced certified grass seed fields present in or near Linn County, OR. Clipping grass seed field polygons with all 91 soil types generated 9,760 unique field by soil type polygons. When restricted to soil types covering at least 5, 10, or 21% of the area of the majority soil type in each individual grass seed field, total numbers of soil types dropped to 85, 82, or 80, and numbers of field by soil type polygons dropped to 7,860, 7,165, or 6,023. When restricted to the majority soil type on each individual grass seed field, total number of soil types dropped to 69 and number of field by soil type polygons dropped to 2,785. After preliminary statistical analyses failed to detect soil type by weed species interactions in all cases of 20 or fewer field by soil type polygons, we restricted our analyses to those 36 soil types present on a minimum 20 or more fields at an extent of 21% or more of the majority soil type's area within each field. These restrictions provided a total of 5,801 field by soil type polygons with which to conduct chi-square tests for interaction of soil type and weed species as classification factors for presence of weeds. We confirmed that these 36 soil types were the most important to examine when we clipped the full set of grass seed fields with these 36 soil types and obtained 9,014 polygons, or over 93% of the total number of polygons obtained when fields were clipped with all 91 soil types.

Our analyses to predict the presence or absence of weeds failed to reject the null hypothesis of freedom from interaction between soil type and weed species for three grasses and five broadleaves (Tables 4 and 5). Average frequencies of occurrence for these eight cases were 0.04, 0.07, 0.04, 0.05, 0.09, 0.03, 0.03, and 0.12 for perennial ryegrass excluding crop cases, reed canarygrass, wheat, catchweed bedstraw, prickly lettuce, pineapple-weed, Himalaya blackberry, and *Rumex* spp., respectively. The failure to detect interactions with soil type for these eight weeds was not a problem of inadequate statistical power (too few cases where the weeds were present) because interactions with soil type were detected for many other weeds whose average frequencies of occurrence

Table 4. Frequency of occurrence at any level of 20 grassy weeds of grass seed crops in 36 soils of Linn County, OR.

Soil types	AGRRE	AGSST & AGSTE[a]	AGSST & AGSTE[b]	AVESA & AVEFA	*Bromus* spp.	DACGL[a]	DACGL[b]	FESAR[a]	FESAR[b]	HOLLA	HOLMO	LOLMU[a]	LOLMU[b]	LOLPE[a]	POAAN	POAPR[a]	POAPR[b]	POATR[a]	POATR[b]	VLPMY
	Grassy weed species																			
	Frequency of weed occurrence at *trace* or greater levels by soil type[c]																			
Amity silt loam	**0.03**	0.22	0.19	0.22	0.24	0.29	0.21	0.72	**0.30**	0.12	**0.03**	0.76	0.69	0.52	**0.54**	**0.09**	**0.09**	**0.49**	**0.49**	**0.01**
Awbrig silty clay loam	**0.02**	0.28	0.19	0.24	0.21	0.37	0.25	0.73	0.28	0.15	0.08	0.74	0.72	0.47	0.39	0.04	0.04	**0.48**	**0.48**	0.04
Bashaw silty clay	**0.03**	0.22	0.19	0.22	0.31	0.41	0.26	0.75	0.31	0.10	**0.02**	0.70	0.67	0.46	**0.49**	0.08	0.08	0.42	0.42	0.04
Bellpine silty clay loam	0.05	**0.62**	**0.48**	0.14	0.29	0.33	0.29	0.67	0.29	**0.48**	**0.52**	0.33	0.33	0.29	0.19	0.05	0.05	0.33	0.33	**0.19**
Camas gravelly sandy loam	**0.14**	**0.12**	**0.07**	0.19	0.21	**0.20**	0.17	0.57	**0.12**	0.07	0.05	0.60	0.49	0.41	0.26	0.02	**0.00**	**0.15**	**0.14**	0.04
Chapman loam	**0.16**	0.20	0.11	0.30	0.33	**0.46**	0.27	0.65	0.19	0.09	**0.01**	0.65	0.60	0.45	0.33	0.04	0.04	0.27	0.27	0.01
Chehalis silty clay loam	**0.14**	**0.15**	**0.08**	0.30	0.25	0.28	0.19	0.64	**0.18**	**0.05**	**0.04**	**0.59**	**0.53**	**0.38**	**0.27**	0.05	0.04	**0.20**	**0.20**	0.02
Clackamas gravelly silt loam	**0.03**	0.27	0.17	0.20	0.27	0.33	**0.14**	0.64	0.21	**0.18**	**0.19**	0.69	0.68	0.55	**0.26**	**0.01**	**0.01**	0.36	0.36	0.03
Cloquato silt loam	**0.21**	0.21	**0.08**	**0.37**	**0.33**	0.35	0.24	0.60	0.20	0.09	**0.04**	0.73	0.66	0.48	0.37	0.04	0.04	**0.26**	**0.26**	0.05
Coburg silty clay loam	0.06	0.24	0.20	**0.32**	0.29	**0.44**	**0.27**	0.75	0.25	0.11	**0.05**	0.67	0.63	0.40	0.39	0.05	0.05	0.39	0.39	0.04
Concord silt loam	0.04	0.19	0.16	0.21	0.20	0.30	0.19	0.72	0.30	0.11	**0.02**	0.75	0.68	0.50	**0.53**	**0.12**	**0.11**	**0.53**	**0.53**	0.02
Conser silty clay loam	0.04	0.20	0.14	0.31	0.24	**0.44**	0.28	0.71	0.30	**0.17**	0.10	0.72	0.66	0.42	0.33	**0.02**	**0.02**	0.43	0.43	0.02
Courtney gravelly silty clay loam	0.05	0.32	0.20	0.23	**0.36**	0.30	0.18	0.78	0.27	**0.22**	**0.20**	0.74	0.73	0.48	0.28	**0.00**	**0.00**	0.39	0.39	0.03
Dayton silt loam	**0.02**	0.26	**0.22**	**0.20**	0.23	0.30	0.23	**0.74**	**0.31**	0.12	**0.04**	**0.74**	**0.69**	**0.52**	**0.55**	**0.10**	**0.10**	**0.52**	**0.52**	**0.02**
Dupee silt loam	0.14	**0.43**	0.30	0.11	0.24	**0.11**	0.08	0.62	0.30	**0.27**	**0.49**	0.59	0.54	0.35	0.24	0.00	0.00	0.19	0.19	**0.16**
Hazelair silty clay loam	0.06	**0.48**	**0.39**	0.24	0.30	0.33	0.27	0.79	0.27	**0.30**	**0.24**	0.58	0.52	0.27	0.42	0.03	0.03	0.36	0.36	0.06
Holcomb silt loam	0.03	0.26	0.23	**0.15**	**0.16**	0.28	0.21	0.75	**0.32**	0.16	**0.05**	0.70	0.67	**0.58**	**0.49**	0.06	0.06	**0.54**	**0.54**	0.01
Jory silty clay loam	0.05	0.34	0.26	0.20	0.25	0.21	0.14	**0.44**	0.18	**0.20**	**0.46**	**0.45**	**0.43**	0.44	**0.18**	0.05	0.04	**0.21**	**0.21**	**0.18**
Malabon silty clay loam	0.09	**0.16**	**0.11**	0.29	0.26	**0.49**	0.25	0.65	0.22	**0.07**	**0.04**	0.58	**0.51**	**0.33**	0.34	0.07	0.07	0.32	0.32	0.02
McAlpin silty clay loam	0.05	0.37	**0.33**	0.23	0.35	**0.16**	0.11	0.67	0.26	**0.25**	**0.46**	0.60	0.60	0.39	**0.21**	0.00	0.00	0.33	0.33	**0.11**
McBee silty clay loam	**0.15**	**0.17**	**0.11**	**0.35**	0.29	0.36	0.26	0.72	0.23	0.09	0.05	0.64	0.60	0.47	0.32	0.07	0.07	0.30	0.30	0.03
Nekia silty clay loam	0.03	**0.32**	0.21	0.20	0.23	**0.15**	**0.08**	**0.48**	0.20	**0.20**	**0.49**	**0.51**	**0.49**	0.39	**0.19**	**0.02**	**0.01**	**0.17**	**0.17**	**0.12**
Newberg fine sandy loam	**0.18**	0.19	**0.09**	0.29	0.31	0.31	0.20	0.61	**0.18**	0.10	**0.02**	0.71	0.66	0.48	0.34	0.07	0.07	**0.24**	**0.24**	0.03
Newberg loam	0.11	0.21	0.10	0.24	0.17	**0.14**	**0.12**	**0.48**	**0.11**	**0.03**	0.05	**0.50**	**0.36**	**0.31**	**0.20**	0.06	**0.01**	**0.14**	**0.13**	0.03
Pengra silt loam	0.05	**0.50**	**0.45**	0.25	**0.50**	0.45	0.35	0.70	0.30	**0.30**	0.10	0.70	0.60	0.55	0.40	0.00	0.00	0.60	0.60	0.05
Salem gravelly silt loam	0.05	0.27	0.22	0.32	0.28	**0.49**	0.28	0.70	0.19	0.11	0.05	0.68	0.61	0.38	0.38	0.01	0.01	0.38	0.38	0.04
Salkum silty clay loam	0.06	**0.40**	0.27	**0.12**	**0.14**	**0.19**	0.12	0.56	0.22	**0.26**	**0.47**	0.59	0.59	0.44	**0.17**	0.01	0.01	**0.14**	**0.14**	**0.12**
Santiam silt loam	**0.03**	**0.40**	**0.29**	0.21	0.21	0.21	0.14	0.64	0.22	**0.22**	**0.29**	0.59	0.52	0.41	0.27	0.03	0.03	**0.21**	**0.21**	0.04
Saturn variant silt loam	0.05	0.29	0.24	0.10	0.29	0.24	0.10	0.52	0.19	0.00	**0.24**	0.86	0.86	0.71	**0.10**	0.05	0.05	0.57	0.57	0.00
Stayton silt loam	0.04	**0.48**	0.22	0.13	0.09	0.13	0.09	0.61	0.26	**0.30**	**0.65**	0.52	0.52	0.35	0.26	0.00	0.00	0.13	0.13	0.09
Waldo silty clay loam	0.12	**0.54**	**0.50**	**0.46**	**0.46**	0.38	0.35	0.88	**0.58**	**0.35**	0.12	0.88	0.88	0.69	0.42	0.04	0.04	**0.77**	**0.77**	0.08
Wapato silty clay loam	**0.18**	0.17	0.12	**0.38**	0.32	0.39	0.25	0.72	0.25	**0.06**	**0.03**	0.75	0.72	0.40	0.32	0.07	0.07	0.38	0.38	0.03
Willamette silt loam	0.04	0.31	**0.26**	0.25	0.32	**0.47**	**0.31**	0.69	0.26	0.08	**0.02**	0.70	0.65	0.37	0.45	**0.12**	**0.12**	0.35	0.35	0.06
Witzel variant very cobbly silt loam	0.06	**0.45**	0.32	0.13	0.32	0.23	0.13	**0.32**	0.19	0.23	**0.55**	0.58	0.52	0.39	0.26	0.00	0.00	**0.13**	**0.13**	**0.13**
Witzel very cobbly loam	0.04	0.39	0.35	0.17	0.30	0.22	0.09	0.48	0.22	0.26	**0.52**	0.39	0.35	0.30	0.22	0.00	0.00	**0.09**	**0.09**	**0.13**
Woodburn silt loam	**0.02**	0.24	0.20	0.25	0.26	0.38	0.25	0.70	0.28	**0.09**	**0.03**	0.72	0.66	0.46	**0.50**	**0.12**	**0.12**	**0.46**	**0.46**	0.02
Mean	0.07	0.24	0.18	0.25	0.26	0.33	0.22	0.68	0.25	0.12	0.09	0.68	0.63	0.45	0.39	0.07	0.06	0.37	0.37	0.04
Number significantly < mean	7	4	6	3	2	6	3	4	4	5	14	4	5	3	8	4	6	11	11	2
Number significantly > mean	7	10	8	5	4	6	2	1	4	14	14	1	1	2	6	5	5	7	7	8

[a] Including cases in which weed was grown as the crop.

[b] Excluding cases in which weed was present only when grown as the crop.

[c] Weeds present in each certified grass seed field anytime from 1994 to 2003 were assigned to all individual soil types covering 21% or more of the area of the majority soil type within each field. Null hypotheses that severity classification for these 20 grasses and 36 soil types were free from interaction were rejected by chi-square tests at the $P \leq 0.05$ level when classified in three categories (*absent*, present only at *trace* levels, or present at greater than *trace* levels), and were also rejected in nearly all cases when weeds were classified simply as absent or present. Individual soil types by weed species whose chi-square tests indicated the presence of significant interaction at the $P \leq 0.05$ level are denoted in **bold** type. Chi-square tests for the additional weed species and soil types present in the overall data set but omitted from this table were not large enough to reject the null hypothesis of independence, and hence those cases can be summarized simply as their averages over soil types and weed species. Omitted grassy weeds and their average frequency of occurrence at any level over all soil types were: LOLPE[b] at 0.04, TYPAR at 0.07, and wheat at 0.04.

Table 5. Frequency of occurrence at any level of 15 broadleaf and other nongrassy weeds of grass seed crops in 36 soils of Linn County, OR.

Soil types	Broadleaf and other nongrassy weed species															
	Amaranthus spp.	ANTCO	CAPBP	HRYRA	CIRAR	CONAR	DAUCA	ECNOR	EQUAR	KICEL	Lowland cudweed	POLPE	SENVU	SINAR	SONAR	Mean over all weeds[a]
	Frequency of weed occurrence at *trace* or greater levels by soil type[b]															
Amity silt loam	0.03	0.09	0.02	0.03	**0.25**	**0.15**	**0.16**	**0.06**	**0.00**	0.03	0.10	0.17	0.18	**0.04**	0.13	0.22
Awbrig silty clay loam	**0.01**	0.07	0.03	**0.07**	0.28	0.18	0.15	0.16	0.03	**0.09**	0.12	0.20	0.14	0.06	0.19	0.23
Bashaw silty clay	0.01	0.10	0.03	0.04	0.31	**0.09**	0.11	**0.08**	0.04	0.06	**0.12**	0.16	0.13	0.03	0.17	0.22
Bellpine silty clay loam	0.00	0.10	0.00	**0.14**	**0.57**	**0.00**	0.14	0.14	0.00	0.00	0.05	0.19	0.05	0.00	0.05	0.22
Camas gravelly sandy loam	0.06	0.09	**0.09**	0.02	0.26	0.19	**0.01**	0.11	0.04	0.02	**0.01**	0.11	**0.31**	0.07	0.14	0.16
Chapman loam	0.06	**0.23**	**0.07**	0.01	**0.46**	**0.40**	0.14	**0.27**	**0.08**	0.06	0.10	0.12	0.25	**0.16**	**0.21**	0.23
Chehalis silty clay loam	**0.09**	**0.18**	**0.06**	0.02	0.36	**0.45**	0.09	0.16	**0.06**	**0.09**	**0.04**	0.15	**0.28**	**0.14**	0.14	0.20
Clackamas gravelly silt loam	**0.00**	0.08	0.02	0.05	0.26	**0.10**	0.11	0.15	0.03	0.02	0.08	0.19	0.18	0.10	0.11	0.20
Cloquato silt loam	**0.11**	0.15	**0.08**	**0.01**	0.34	**0.47**	**0.08**	**0.22**	0.04	**0.10**	**0.02**	0.13	**0.29**	**0.10**	0.13	0.23
Coburg silty clay loam	0.03	0.14	0.03	0.05	0.35	0.22	0.16	**0.18**	**0.06**	0.07	**0.13**	0.19	0.20	0.08	**0.21**	0.23
Concord silt loam	0.04	**0.07**	0.02	0.02	0.27	0.14	0.12	**0.06**	0.01	0.04	0.12	0.20	0.15	0.03	0.12	0.22
Conser silty clay loam	0.04	0.15	0.03	0.04	0.36	0.22	0.15	0.16	0.04	0.05	**0.14**	0.21	0.21	0.06	**0.22**	0.23
Courtney gravelly silty clay loam	0.01	0.09	0.01	**0.08**	0.29	**0.06**	0.17	0.20	0.03	**0.00**	0.13	**0.24**	0.21	0.06	0.14	0.22
Dayton silt loam	**0.02**	**0.06**	**0.01**	0.04	**0.22**	**0.11**	0.13	**0.06**	**0.01**	**0.03**	**0.12**	0.16	0.17	**0.04**	0.14	0.22
Dupee silt loam	0.00	0.14	0.00	0.08	0.35	0.11	0.14	0.11	0.03	0.00	0.03	0.08	0.14	0.03	0.03	0.19
Hazelair silty clay loam	0.00	0.09	0.00	**0.21**	0.24	0.12	0.06	0.09	0.06	0.00	0.12	0.18	0.06	0.00	0.12	0.22
Holcomb silt loam	0.01	**0.06**	0.01	**0.09**	**0.14**	**0.08**	0.15	**0.07**	0.01	**0.01**	**0.12**	0.14	0.19	0.06	0.16	0.22
Jory silty clay loam	0.00	0.18	0.01	0.05	0.34	**0.00**	0.06	**0.28**	0.01	**0.00**	**0.01**	0.10	0.14	0.03	**0.05**	0.18
Malabon silty clay loam	0.05	0.14	0.05	0.03	**0.41**	**0.27**	0.15	**0.21**	**0.05**	0.06	0.07	**0.11**	0.23	0.09	**0.21**	0.21
McAlpin silty clay loam	0.00	0.18	0.00	**0.11**	0.30	**0.04**	0.05	0.23	0.05	0.00	0.02	0.21	**0.05**	0.05	**0.04**	0.20
McBee silty clay loam	0.06	**0.21**	**0.07**	0.03	0.35	**0.40**	0.13	0.18	0.05	**0.13**	0.06	0.17	0.21	**0.12**	0.13	0.23
Nekia silty clay loam	**0.01**	**0.21**	0.02	0.06	0.37	**0.00**	0.08	**0.31**	0.01	**0.00**	**0.01**	**0.07**	0.16	0.03	**0.04**	0.17
Newberg fine sandy loam	**0.07**	**0.17**	**0.10**	**0.00**	0.29	**0.39**	0.10	0.17	0.03	0.05	**0.03**	0.16	**0.26**	0.08	0.16	0.21
Newberg loam	0.07	0.14	0.06	0.02	0.21	0.29	**0.04**	0.09	0.05	0.06	0.03	0.09	0.20	0.09	0.10	0.14
Pengra silt loam	0.00	0.15	0.00	0.05	0.40	**0.00**	0.20	0.10	0.00	0.00	0.10	0.10	0.10	0.15	0.20	0.26
Salem gravelly silt loam	0.05	0.09	0.04	0.04	0.42	0.30	0.20	**0.34**	**0.08**	0.08	0.08	0.11	0.22	**0.14**	0.15	0.23
Salkum silty clay loam	0.00	0.16	0.00	0.06	0.28	**0.01**	0.09	0.07	0.01	**0.00**	**0.01**	**0.06**	0.15	**0.00**	**0.01**	0.17
Santiam silt loam	0.00	0.10	0.00	0.08	0.30	**0.01**	0.14	0.19	0.00	0.00	0.04	**0.04**	0.12	0.04	**0.05**	0.18
Saturn variant silt loam	0.00	0.05	0.00	0.00	0.19	**0.00**	0.10	0.00	0.00	0.00	0.00	0.19	0.19	0.00	0.00	0.19
Stayton silt loam	0.00	0.13	0.04	0.00	0.48	**0.00**	0.17	0.17	0.00	0.00	0.04	0.09	0.09	0.04	0.04	0.18
Waldo silty clay loam	0.00	0.00	0.00	**0.12**	0.46	0.12	0.12	0.15	0.04	0.04	0.08	**0.35**	0.12	0.04	0.15	0.32
Wapato silty clay loam	0.06	**0.19**	0.06	**0.00**	0.41	**0.45**	0.17	0.18	**0.07**	**0.10**	0.08	**0.35**	0.26	0.12	0.16	0.25
Willamette silt loam	0.06	0.14	0.02	0.03	0.39	**0.12**	0.13	0.10	0.01	0.08	0.08	0.21	0.18	0.06	0.15	0.23
Witzel variant very cobbly silt loam	0.00	**0.29**	0.06	0.03	0.45	**0.00**	0.16	0.26	0.00	0.00	0.00	0.16	0.10	0.06	**0.00**	0.19
Witzel very cobbly loam	0.00	0.17	0.09	0.00	0.39	**0.00**	0.04	**0.30**	0.00	0.00	0.00	0.17	0.09	0.13	0.00	0.17
Woodburn silt loam	0.03	**0.09**	0.02	0.03	0.31	**0.15**	0.13	**0.06**	**0.01**	0.06	0.09	0.14	0.16	0.05	0.14	0.22
Mean	0.04	0.12	0.03	0.04	0.31	0.20	0.13	0.14	0.03	0.05	0.08	0.16	0.19	0.07	0.14	0.21
Number significantly < mean	4	4	1	3	3	19	3	6	3	6	7	4	1	3	6	—
Number significantly > mean	3	7	6	7	3	7	1	8	6	5	5	3	4	5	4	—

[a] Soil type means in this column were averaged over all 20 grassy weeds from Table 4 and all 15 broadleaf and nongrassy weeds from this table.

[b] Weeds present in each certified grass seed field anytime from 1994 to 2003 were assigned to all individual soil types covering 21% or more of the area of the majority soil type within each field. Null hypotheses that severity classification for these 15 broadleaf and other nongrassy weeds and 36 soil types were free from interaction were rejected by chi-square tests at the $P \leq 0.05$ level when classified in three categories (*absent*, present only at *trace* levels, or present at greater than *trace* levels), and were also rejected in nearly all cases when weeds were classified simply as absent or present. Individual soil types by weed species whose chi-square tests indicated the presence of significant interaction at the $P \leq 0.05$ level are denoted in **bold** type. Chi-square tests for the additional weed species and soil types present in the overall data set but omitted from this table were not large enough to reject the null hypothesis of independence, and hence those cases can be summarized simply as their averages over soil types and weed species. Omitted broadleaf and other nongrassy weeds and their average frequency of occurrence at any level over all soil types were: GALAP at 0.05, LACSE at 0.09, MATMT at 0.03, RUBDI at 0.03, and RUMOB & RUMCR at 0.12.

were similarly low (e.g., *Amaranthus* spp, shepherd's-purse, common catsear, field horsetail, Kentucky bluegrass, and rattail fescue all with average frequencies of occurrence from 0.03 to 0.07). The two weed species most often showing significant interaction with soil type were German velvetgrass and field bindweed. These were the two weed species showing strongest Moran's I spatial autocorrelation and Getis-Ord General G high/low clustering of weed severity. Field bindweed was the second most commonly occurring broadleaf weed, with an average frequency of 0.20, and occurred less often than expected on 19 of 36 soil types and more often than expected on 7 of 36 soil types (Table 5). Canada thistle was the most commonly occurring broadleaf weed, with an average frequency of 0.31, but occurred less often than expected in only three cases and more often than expected in another three cases. Among the grassy weeds, German velvetgrass was relatively uncommon, with an average frequency of only 0.09, but occurred more often than expected on 14 soil types and less often than expected on another 14 soil types (Table 4). Of the 20 grasses with significant interaction between soil type and weed species, only four occurred less often on average than German velvetgrass. Other grassy weeds for which interactions between soil type and weed species were relatively common included roughstalk bluegrass (frequency in 11 soils significantly less than average and frequency in five soils greater than average), common velvetgrass (frequency in five soils less than average and frequency in 14 soils greater than average), quackgrass, *Agrostis* spp., and annual bluegrass.

In an attempt to visualize contrasts in frequency of weed occurrence among weed species and soil types, we generated Fitch-Margoliash tree diagrams (Fitch and Margoliash 1967) of the average distance among weed species and soil types (Figures 2 and 3). Total distance (length of horizontal lines) between pairs of weeds (or soils) indicated how similar/dissimilar the pairs were, whereas number of nodes in the tree between pairs indicated how many other weeds (or soils) were more closely linked to members of the pair than the pair members themselves were linked. Because tree branches are free to rotate, mere proximity of species (or soils) labels within the tree do not necessarily indicate closeness. Among the weeds also grown as crops, roughstalk bluegrass, Kentucky bluegrass, and Italian ryegrass all graphed with the crop cases included or excluded as adjacent nodes on the tree (Figure 2). Separation between crop cases included vs. excluded was four nodes for *Agrostis* spp., eight nodes for orchardgrass, and nine nodes for tall fescue. This separation indicated the presence of substantial differences among soils on which these three species were recently grown as crops and on which they appeared as weeds. German velvetgrass and common velvetgrass graphed adjacent to each other, despite a total distance apart that was larger than for most other weeds and their closest neighbors (data not shown). Tall fescue, including crop cases, was most closely linked to Italian ryegrass. Many broadleaf weeds most closely grouped with other broadleaves, whereas others appeared in groups with grasses. Shepherd's-purse, *Amaranthus* spp., field horsetail, and sharppoint fluvellin were all closely linked, and were next most closely grouped with Kentucky bluegrass. Weeds most similar to Canada thistle were *Agrostis* spp. including crop cases and orchardgrass including crop cases at two nodes, annual bluegrass and *Bromus* spp. at three nodes, and tall fescue excluding crop cases and roughstalk bluegrass at four nodes. Weeds most similar to field bindweed were common groundsel (*Senecio vulgaris* L. SENVU) at one node apart; western wildcucumber and ladysthumb at three nodes; mayweed chamomile at four nodes; and wild carrot, common velvetgrass, German velvetgrass, and orchardgrass excluding crop cases at five nodes. The general appearance of the tree diagram for soil types was one of more uniform dispersion than the diagram for weed species. The diagram for soil types was most noticeably lacking elements with extremely high similarity to each other (Figure 3). The most closely linked soils were Amity, Concord, and Dayton. Other pairs of relatively closely linked soils were Coburg and Conser, Nekia and Jory, Newberg and Cloquato, and Courtney and Clackamas. Because soil chemical and physical properties can be expected to influence both the farmers' choice of crops and the success of weeds within those crops and during fallow periods between crops, interactions between weed species and soil types will inherently be complex.

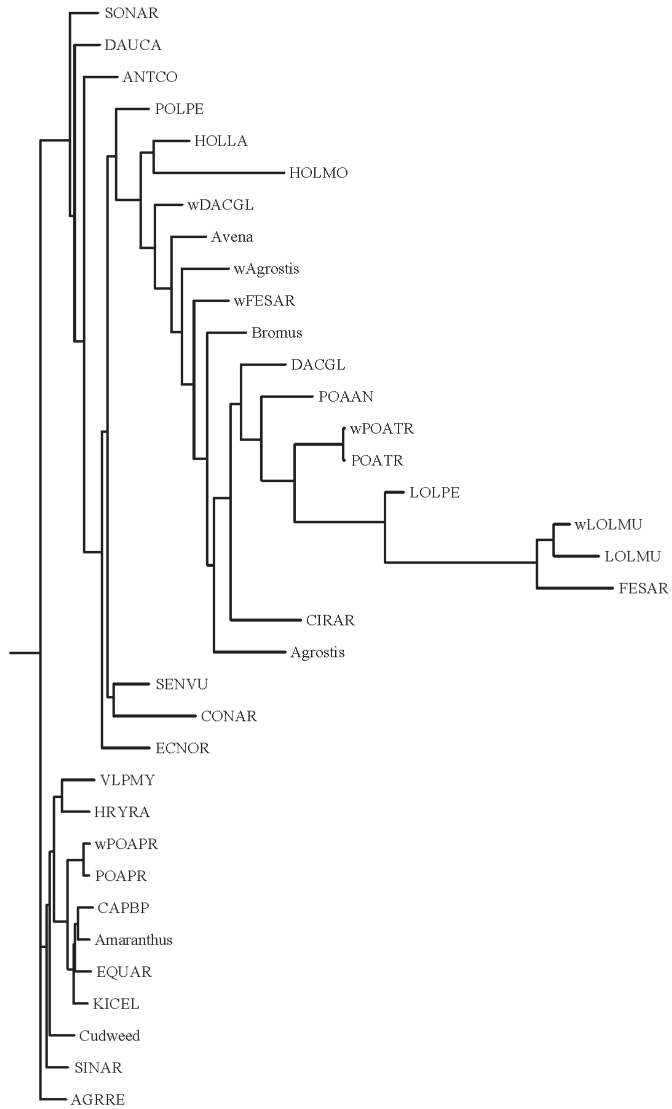


Figure 2. Fitch-Margoliash tree diagrams of distance between 35 weed species based on average differences among 36 soil types over a 10-yr period from weed by soil type frequency of occurrence at any level matrix.

Although weeds by definition are plants well adapted to life in areas under intensive human management, they nevertheless display a wide variety of survival adaptations. Many of the

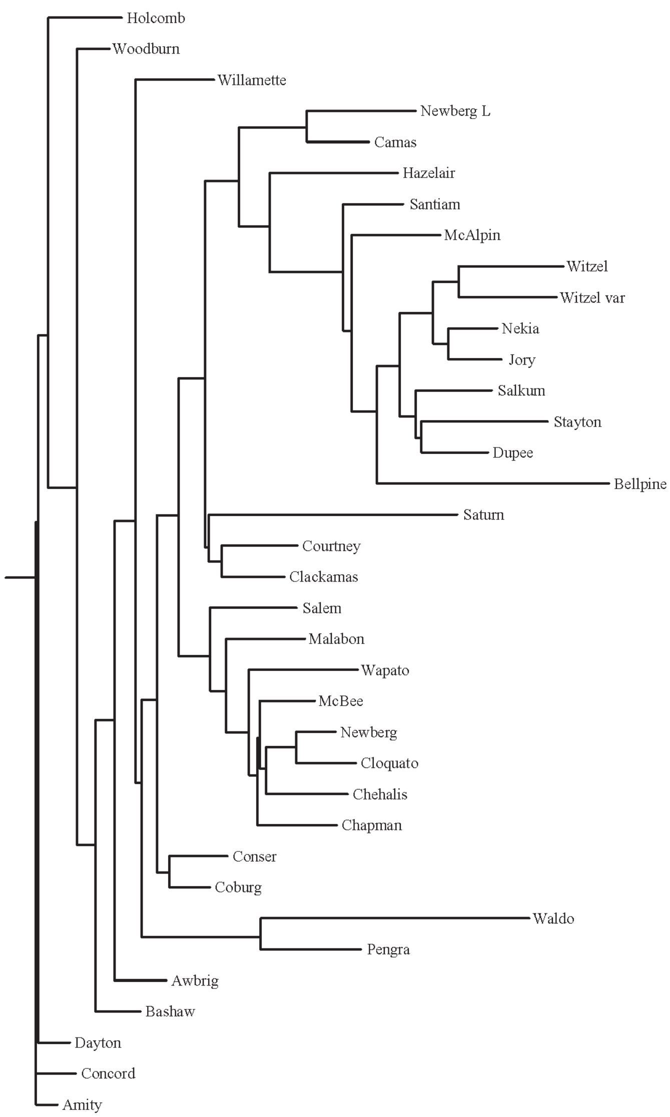


Figure 3. Fitch-Margoliash tree diagrams of distance between 36 soil types based on average differences among 35 weed species over a 10-yr period from weed by soil type frequency of occurrence at any level matrix.

36 weeds in our study were relatively unaffected by soil type and can therefore be viewed as generalists. Defining a soil type generalist as a weed that interacted with soil type in less than one-third of all cases, 14 of 23 grasses and 17 of 23 broadleaves were generalists. The other extreme of soil type specialists was represented by weeds that interacted with soil type in more than two-thirds of all cases, specifically field bindweed and German velvetgrass. Clearly different weed management strategies ought to be developed for the soil type generalists likely to appear anywhere grass seed is grown in western Oregon and soil type specialists generally absent from certain soils but commonly present on others. Because these two species also showed the strongest spatial autocorrelation, it is a reasonable inference that weeds possessing strong spatial autocorrelation are soil type specialists, at least when data are collected from a mature agricultural industry with relatively few newly invading weeds.

Principal Components Analysis (PCA), Redundancy Analysis (RDA), Correspondence Analysis (CA), and Canonical Correspondence Analysis (CCA). In an attempt to extract dominant features of the interaction between weed species and soil types in simpler terms, we conducted multivariate analyses using PCA, RDA, CA, and CCA on occurrence and severity of weeds. Explanatory factors added in RDA and CCA models included crop species, soil type, and four soil properties: clay content, cation exchange capacity (CEC), pH, and hydraulic conductivity. Because software limitations in ArcGIS had restricted PCA to a maximum of 20 weeds at a time, we exported data into the programming environment R (version 2.6.0) where PCA, RDA, CA, and CCA could be run on the full set of data. Unconstrained RDA is simply PCA, and the first two eigenvectors accounted for a total of only 19.3% of the inertia (or variance) in weed occurrence (Table 6) and 27.0% of it in weed severity (Table 7). The first 8 of 36 PCA eigenvectors accounted for 47.9 and 58.6% of the total variance in weed occurrence and weed severity, respectively. Selecting all eigenvectors explaining more than an average one 36th of the total variance, the first 15 eigenvectors accounted for 70.6% of the variance in weed occurrence, and the first 12 eigenvectors accounted for 71.1% of the variance in weed severity. These values of 15 dimensions for weed occurrence and 12 dimensions for weed severity can be viewed as representing the practical dimensionality of the data, and indicate that large numbers of variables (15 for occurrence and 12 for severity) would be needed to account for the most of the behavior of weeds in the 10 years of certified grass seed production. Bi-plot ordinations of species distribution in the first two PCA dimensions highlighted some major differences between patterns of weed occurrence and weed severity (Figures 4 and 5). For weed severity, 10 species differed sufficiently from the remaining cluster to stand out in the overall plot, with annual bluegrass, Italian ryegrass excluding crop cases, and roughstalk bluegrass excluding crop cases being most unique, followed in decreasing distance from the cluster by tall fescue excluding crop cases, *Bromus* spp., *Avena* spp., common velvetgrass, Canada thistle, German velvetgrass, and field bindweed (Figure 5). Ranges of the two axes in weed occurrence bi-plots were only about half as large as ranges in weed severity plots, and fewer species were tightly clustered (Figure 4). In addition to the 10 most unique species in the severity bi-plot ordination, perennial sowthistle (*Sonchus arvensis* L. SONAR), common groundsel, orchardgrass excluding crop cases, western wildcucumber, mayweed chamomile, reed canarygrass, quackgrass, wild mustard, wild carrot, *Agrostis* spp. excluding crop cases, Kentucky bluegrass excluding crop cases, *Rumex* spp., and ladysthumb also stood out from the 12 remaining weeds clustered together in the occurrence bi-plot. When CA was used rather than PCA, weeds were more uniformly dispersed in bi-plot ordinations for both occurrence and severity (data not shown). Similar differences between CA and PCA existed in the unconstrained eigenvalues, with each individual higher order CA eigenvalue (1 to 2 for weed occurrence and 1 to 4 for weed severity) explaining less than 70% of the variance explained by the corresponding PCA eigenvalues (Tables 6 and 7).

Soil type was the most successful variable added in RDA or CCA of either weed occurrence or severity, but even it only explained 6.2 and 7.6% of the total RDA variance in weed occurrence and severity, respectively (Tables 6 and 7). Dummy crop variables (defined as equal to 1 for fields in which a given crop species had been grown at any time over

Table 6. Constrained and unconstrained inertia in RDA and CCA of occurrence of 36 weeds over a 10-yr period using soil type, crop, and soil chemical/physical properties as constraining variables, and higher order eigenvalues.

Model type[b]	Constraining factors	Inertia (variance)		Unconstrained eigenvalues			Constrained eigenvalues[a]			
		Constrained	Unconstrained	First	Second	Sum 1–8 of 36	First	Second	Third	Fourth
PCA	none	—	4.1703	0.4596	0.3465	1.9995	—	—	—	—
RDA	36 soil types	0.2607	3.9096	0.4232	0.2873	1.8253	0.0845	0.0724	0.0210	0.0156
RDA	5 crops	0.2287	3.9416	0.4131	0.2936	1.8263	0.1292	0.0528	0.0314	0.0118
RDA	soil properties	0.0462	4.1242	0.4557	0.3275	1.9614	0.0326	0.0095	0.0034	0.0007
RDA	soil type + crop	0.4651	3.7052	0.3794	0.2395	1.6725	0.1555	0.0865	0.0733	0.0344
RDA	soil type + soil properties	0.2628	3.9075	0.4231	0.2871	1.8242	0.0851	0.0729	0.0212	0.0157
RDA	crop + soil properties	0.2711	3.8992	0.4092	0.2772	1.7917	0.1324	0.0561	0.0405	0.0200
RDA	soil type + crop + soil properties	0.4672	3.7031	0.3793	0.2390	1.6712	0.1557	0.0870	0.0734	0.0349
CA	none	—	4.9503	0.2746	0.2432	1.6171	—	—	—	—
CCA	36 soil types	0.2660	4.6840	0.2225	0.1941	1.4549	0.0888	0.0673	0.0146	0.0135
CCA	5 crops	0.1461	4.8042	0.2638	0.2175	1.5537	0.0666	0.0538	0.0153	0.0071
CCA	soil properties	0.0523	4.8980	0.2487	0.2354	1.5746	0.0399	0.0089	0.0029	0.0006
CCA	soil type + crop	0.3958	4.5545	0.2104	0.1845	1.4045	0.1003	0.0903	0.0445	0.0392
CCA	soil type + soil properties	0.2690	4.6810	0.2222	0.1937	1.4533	0.0898	0.0681	0.0146	0.0135
CCA	crop + soil properties	0.1967	4.7537	0.2371	0.2101	1.5122	0.0713	0.0597	0.0311	0.0163
CCA	soil type + crop + soil properties	0.3987	4.5516	0.2099	0.1843	1.4027	0.1010	0.0907	0.0449	0.0395

[a] Total number of constrained eigenvectors varied with model, and was four for soil properties, five for crops, nine for crops + soil properties, and 36 for all other cases. Kentucky bluegrass and roughstalk bluegrass were excluded from dummy crop variables because of their extremely small number of cases.

[b] Abbreviations: CA = Correspondence Analysis; CCA = Canonical Correspondence Analysis; PCA = Principal Components Analysis; RDA = Redundancy Analysis.

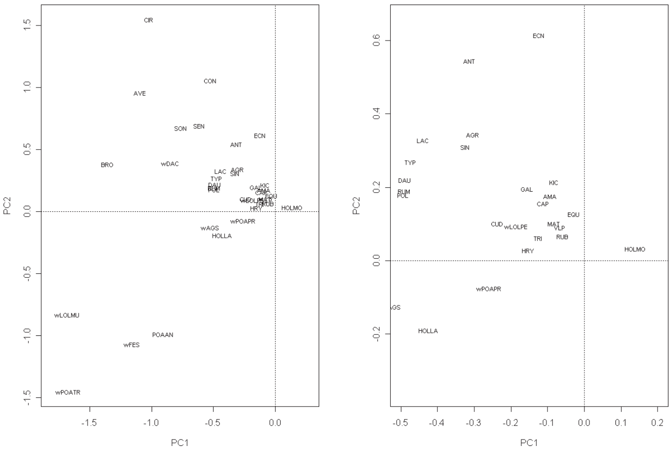
the decade and otherwise equal to 0) for *Agrostis* spp., orchardgrass, tall fescue, Italian ryegrass, and perennial ryegrass together explained 5.5 and 7.2% of the total variance in weed occurrence and severity, respectively. Dummy soil type and crop variables were relatively independent, and models with both factors combined explained 95.0 and 93.4% of the sum of the separate (single variable) soil type and crop variances for weed occurrence and severity, respectively. Plots of CCA for weed occurrence and severity as affected by soil type and crop both identified similar weeds as behaving most uniquely (Figures 6 and 7). German velvetgrass was furthest from the centers of the ordination axes in both cases, followed in order of decreasing distance by rattail fescue, common velvetgrass, and weedy perennial ryegrass (i.e., excluding crop cases). Vectors representing Nekia and Jory soil types and *Agrostis* spp. as crop type pointed in the same general direction as German velvetgrass, rattail fescue, and weedy perennial ryegrass (vector data not shown). Weedy tall fescue and roughstalk bluegrass plotted close to each other for both occurrence and severity, with the perennial ryegrass crop vector pointing close to both of them. Weeds most closely linked to field bindweed in both occurrence and severity included shepherd's-purse, sharppoint fluvellin, and field horsetail. Annual bluegrass and weedy Italian ryegrass plotted in the same general direction as weedy roughstalk bluegrass for both occurrence and severity, although much closer to the centers of the ordination axes. In contrast to the crops variable, soil chemical/physical properties variables were highly colinear with soil type, but this was to be expected because each soil type was assigned only a single value of each of the soil property variables. The four soil property variables by themselves only explained 17.8 and 18.1% as much of the total variance in weed occurrence and severity, respectively, as the 36 soil types explained. Adding soil properties variables to

Table 7. Constrained and unconstrained inertia in RDA and CCA of maximum observed severity of 36 weeds over a 10-yr period using soil type, crop, and soil chemical/physical properties as constraining variables, and higher order eigenvalues.

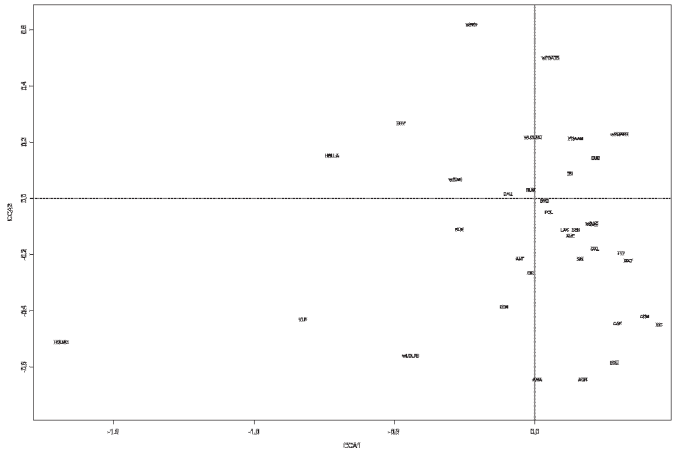
Model type[b]	Constraining factors	Inertia (variance)		Unconstrained eigenvalues			Constrained eigenvalues[a]			
		Constrained	Unconstrained	First	Second	Sum 1–8 of 36	First	Second	Third	Fourth
PCA	none	—	4.9285	0.8581	0.4713	2.8898	—	—	—	—
RDA	36 soil types	0.3735	4.5550	0.7299	0.4269	2.5948	0.1799	0.0824	0.0253	0.0183
RDA	5 crops	0.3538	4.5747	0.6971	0.4339	2.5984	0.2273	0.0813	0.0297	0.0116
RDA	soil properties	0.0675	4.8610	0.8354	0.4645	2.8285	0.0476	0.0159	0.0032	0.0008
RDA	soil type + crop	0.6790	4.2500	0.5942	0.3989	2.3504	0.3199	0.1132	0.0883	0.0421
RDA	soil type + soil properties	0.3758	4.5527	0.7295	0.4266	2.5932	0.1805	0.0832	0.0254	0.0184
RDA	crop + soil properties	0.4141	4.5144	0.6797	0.4261	2.5441	0.2397	0.0845	0.0434	0.0216
RDA	soil type + crop + soil properties	0.6813	4.2472	0.5938	0.3987	2.3490	0.3203	0.1134	0.0889	0.0424
CA	none	—	5.0824	0.3193	0.2826	1.7441	—	—	—	—
CCA	36 soil types	0.3116	4.7707	0.2291	0.2228	1.5326	0.1145	0.0848	0.0176	0.0137
CCA	5 crops	0.1826	4.8998	0.2963	0.2451	1.6508	0.0929	0.0630	0.0162	0.0068
CCA	soil properties	0.0597	5.0227	0.3036	0.2559	1.6962	0.0457	0.0108	0.0024	0.0008
CCA	soil type + crop	0.4651	4.6173	0.2159	0.2046	1.465	0.1423	0.1116	0.0492	0.0393
CCA	soil type + soil properties	0.3144	4.7679	0.2288	0.2223	1.5313	0.1151	0.0859	0.0176	0.0138
CCA	crop + soil properties	0.2395	4.8429	0.2679	0.2307	1.6034	0.0966	0.0741	0.0337	0.0169
CCA	soil type + crop + soil properties	0.4679	4.6145	0.2152	0.2045	1.4635	0.1426	0.1125	0.0496	0.0394

[a] Total number of constrained eigenvectors varied with model, and was four for soil properties, five for crops, nine for crops + soil properties, and 36 for all other cases. Kentucky bluegrass and roughstalk bluegrass were excluded from dummy crop variables because of their extremely small number of cases.

[b] Abbreviations: CA = Correspondence Analysis; CCA = Canonical Correspondence Analysis; PCA = Principal Components Analysis; RDA = Redundancy Analysis.



Figures 4. Bi-plot ordination of principal component analysis of weed occurrence by fields over the 10-yr period. Entire ordination is shown on the left, and a zoom-in to the center data cluster is shown on the right. Species ID have been shortened to three letters where that introduced no ambiguity, and a "w" preceding the Bayer code ID indicates exclusion of cases where the species was grown as a crop.

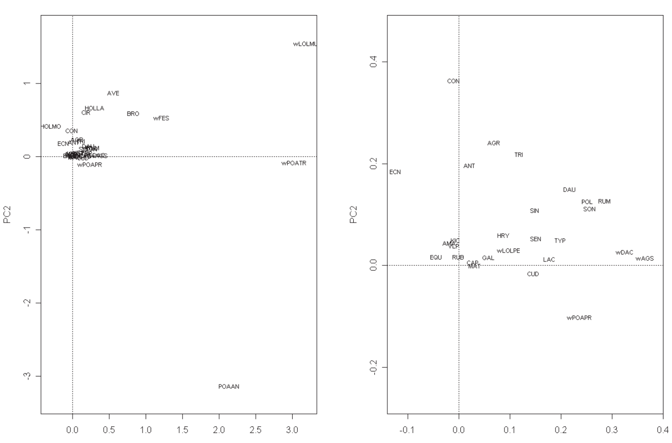


Figures 6. Bi-plot ordination of canonical correspondence analysis of weed occurrence by fields over the 10-yr period using dummy variables for 36 soil types and five crop species. Species ID have been shortened to three letters where that introduced no ambiguity, and a "w" preceding the Bayer code ID indicates exclusion of cases where the species was grown as a crop.

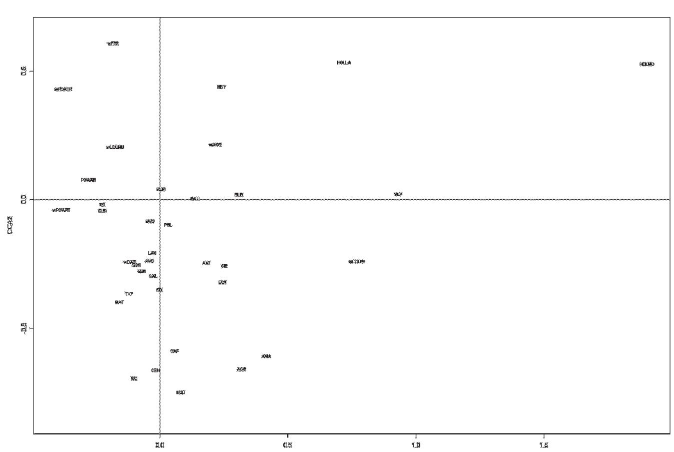
models already possessing a soil type variable only increased the total variance explained by approximately 1%. Adding soil type, crop, and soil properties variables in CCA models of weed occurrence and severity gave results generally similar to those in RDA models, although each variable in CCA explained a slightly smaller proportion of the total variance. Soil types most closely linked in RDA ordinations included Jory and Nekia; Chapman, McBee, Newberg fine sandy loam, Cloquato, and Malabon; Willamette, Awbrig, Waldo, Bashaw, Concord, Woodburn, and Amity; Courtney and Hazelair; and Santiam, McAlpin, Bellpine, and Salkum (data not shown).

The presence of detectable soil type and crop variable effects on weed occurrence and severity patterns suggests that, to a limited extent, both soils present within fields and crops grown on those fields acted to define weed problems. Although this is certainly not a surprising finding, our successful detection of those patterns is an encouraging confirmation of the validity of the procedures we used to convert field inspection reports into a GIS and analyze the data. Despite this success, the inability of dummy soil type and crop variables to constrain the remaining 88% of variance in weed occurrence and 86% in weed severity reminds us that many other factors were at work in determining which weeds were present, which were absent, and how severe those weeds present actually were in certified grass seed fields. Herbicide treatment programs and crop rotation sequences are two major unaccounted factors, and unfortunately little public data exist for identifying them. We do, however, have data on age of grass seed stands, seasonal planting date, and duration of the rotational period between certified grass seed crops for fields in our GIS, and multivariate analysis of the effects of those variables on weed occurrence and severity is currently being prepared for publication.

Additional analyses of the four soil chemical/physical properties variables revealed that despite the relatively small size of their effects on weed occurrence and severity, those effects nonetheless were often statistically significant (data not shown). Because values for clay content, hydraulic conduc-



Figures 5. Bi-plot ordination of principal component analysis of maximum weed severity by fields over the 10-yr period. Entire ordination is shown on the left, and a zoom-in to the center data cluster is shown on the right. Species ID have been shortened to three letters where that introduced no ambiguity, and a "w" preceding the Bayer code ID indicates exclusion of cases where the species was grown as a crop.



Figures 7. Bi-plot ordination of canonical correspondence analysis of maximum weed severity by fields over the 10-yr period using dummy variables for 36 soil types and five crop species. Species ID have been shortened to three letters where that introduced no ambiguity, and a "w" preceding the Bayer code ID indicates exclusion of cases where the species was grown as a crop.

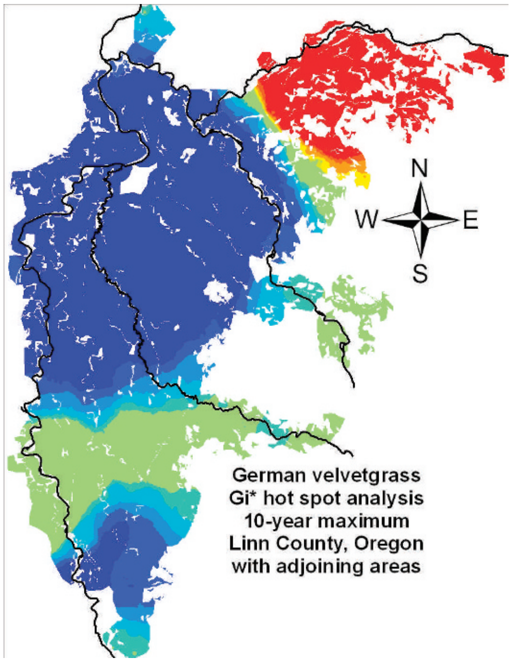


Figure 8. Gi* hot-spot analysis for 10-yr maximum severity of German velvetgrass using 8 km fixed distance neighborhood method. Dark blue, blue, light blue, dark aqua, and aqua colors denote areas with significantly lower than expected weed severity at the P = 0.0001, 0.001, 0.01, 0.05, and 0.1 levels, respectively. Bright red, red, orange, and orange-yellow, and yellow denote areas with significantly higher than expected weed severity at the P = 0.0001, 0.001, 0.01, 0.05, and 0.1 levels, respectively. Green areas are neither significantly higher nor lower than expected in weed severity. Scale is 1:275,000 if map is printed as a full page.

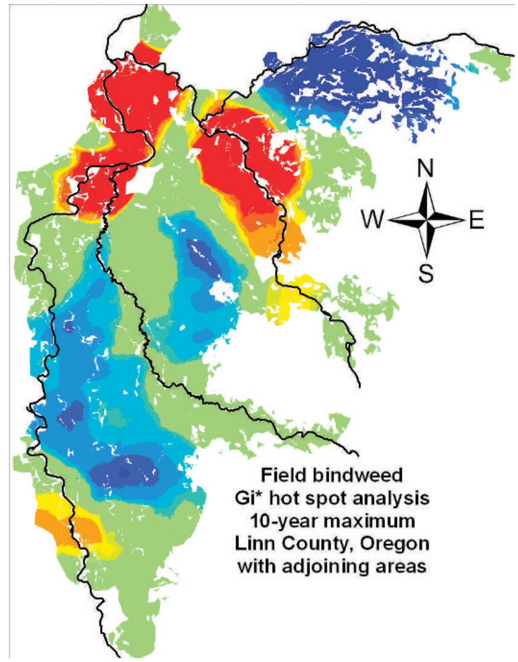


Figure 9. Gi* hot-spot analysis for 10-yr maximum severity of field bindweed using 4 km fixed distance neighborhood method. Dark blue, blue, light blue, dark aqua, and aqua colors denote areas with significantly lower than expected weed severity at the P = 0.0001, 0.001, 0.01, 0.05, and 0.1 levels, respectively. Bright red, red, orange, and orange-yellow, and yellow denote areas with significantly higher than expected weed severity at the P = 0.0001, 0.001, 0.01, 0.05, and 0.1 levels, respectively. Green areas are neither significantly higher nor lower than expected in weed severity. Scale is 1:275,000 if map is printed as a full page.

tivity, CEC, and pH came from USDA–NRCS soil surveys rather than measurements within our individual fields, they were assigned only a single value for each soil type and a limited number of values for each grass seed field (calculated as the unweighted average of the values for all soil types covering 21% or more of the area of the majority soil type within an individual field). This limited the precision of our estimates of soil properties and restricted interpretation of analyses. Nevertheless, analyses indicated that basic soil physical and chemical properties could function as useful surrogates for part of the soil type effect on weed occurrence and severity. To better understand the relationship between soil properties and weed occurrence and severity data, we analyzed clustering patterns of four soil properties using fixed distance weighting methods to determine the distance for peak significance and the maximum range of significance for Moran's I spatial autocorrelation. Distances for peak significance in spatial autocorrelation of clay content, hydraulic conductivity, CEC, and pH were 19, 4, 53, and 8 km, whereas maximum ranges of significance for these variables were 43, 30, 67, and 27 km. Distances for peak significance and maximum range of significance for hydraulic conductivity and pH were less than average distances for peak significance and maximum range of significance for severity of the 43 weeds. Corresponding distances for clay content and CEC were greater than averages for the weeds. None of the distances for spatial autocorrelation of soil properties fell outside of the observed range of distances for spatial autocorrelation of weed severity. Although clay content, hydraulic conductivity, CEC, and pH only partially substituted for the effects of our 36 soil types, their inclusion in future GIS data compilations might be warranted if costs were incidental because the data already existed and merely had to organized and imported into a GIS.

Multivariate analysis offers the potential to simplify large, complex data sets by identifying variables that behave similarly, allowing data to be regrouped into smaller, somewhat more easily visualized entities. Dimensionality of our data was high, with the best 15 eigenvectors for occurrence and 12 eigenvectors for severity still leaving approximately 29% of variation in weeds unrepresented. Our primary finding from multivariate analysis was that the combination of our two best explanatory variables, soil type and crop species grown in the field, still left 86% of the variation in weed severity and 88% of the variation in weed occurrence unexplained. Although soil chemical and physical properties measured at the soil type level rather than within individual fields were poor substitutes for the full list of soil types, they nonetheless were capable of explaining a small but significant amount of the variation in weed occurrence and severity, and might explain more if measured on an individual soil type by field basis. PCA of weed severity identified the 10 most uniquely behaving weeds of western Oregon grass seed crops as annual bluegrass, Italian ryegrass, roughstalk bluegrass, tall fescue, *Bromus* spp., *Avena* spp., common velvetgrass, Canada thistle, German velvetgrass, and field bindweed. Multivariate clustering of the remaining 33 weeds indicated that they tended to be present or absent at relatively similar levels of severity within individual fields. In contrast, the 10 most unique weeds must each be studied individually if we desire to understand the role that crop management practices, soil type, and past field history play in determining

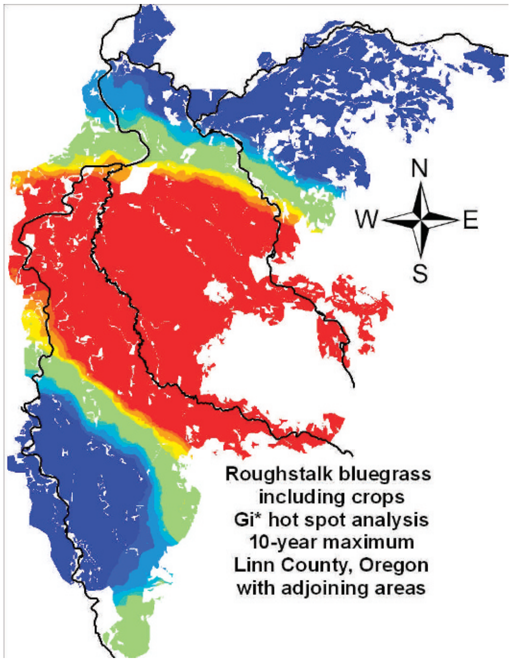


Figure 10. Gi* hot-spot analysis for 10-yr maximum severity of roughstalk bluegrass grass using 14 km fixed distance neighborhood method. Dark blue, blue, light blue, dark aqua, and aqua colors denote areas with significantly lower than expected weed severity at the P = 0.0001, 0.001, 0.01, 0.05, and 0.1 levels, respectively. Bright red, red, orange, and orange-yellow, and yellow denote areas with significantly higher than expected weed severity at the P = 0.0001, 0.001, 0.01, 0.05, and 0.1 levels, respectively. Green areas are neither significantly higher nor lower than expected in weed severity. Scale is 1:275,000 if map is printed as a full page.

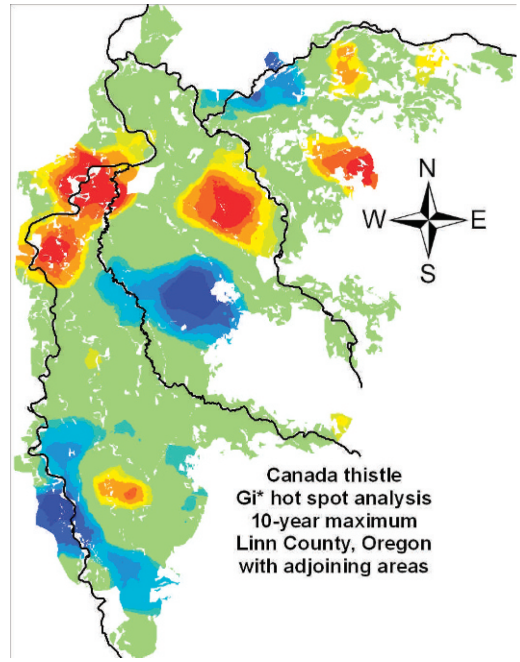


Figure 12. Gi* hot-spot analysis for 10-yr maximum severity of Canada thistle using 4 km fixed distance neighborhood method. Dark blue, blue, light blue, dark aqua, and aqua colors denote areas with significantly lower than expected weed severity at the P = 0.0001, 0.001, 0.01, 0.05, and 0.1 levels, respectively. Bright red, red, orange, and orange-yellow, and yellow denote areas with significantly higher than expected weed severity at the P = 0.0001, 0.001, 0.01, 0.05, and 0.1 levels, respectively. Green areas are neither significantly higher nor lower than expected in weed severity. Scale is 1:275,000 if map is printed as a full page.

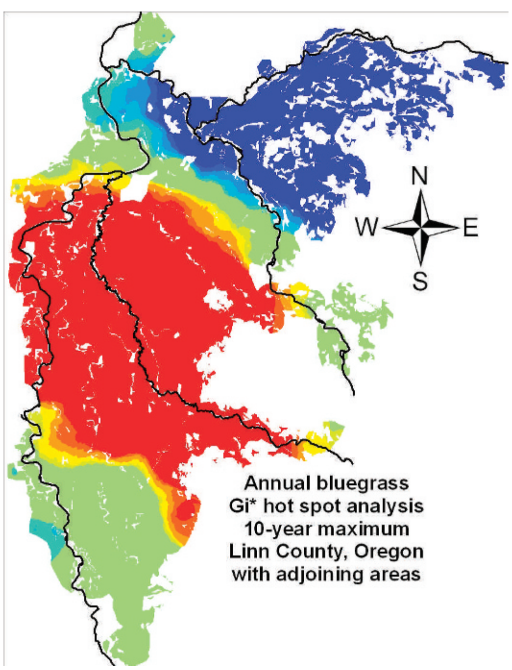


Figure 11. Gi* hot-spot analysis for 10-yr maximum severity of annual bluegrass using 14 km fixed distance neighborhood method. Dark blue, blue, light blue, dark aqua, and aqua colors denote areas with significantly lower than expected weed severity at the P = 0.0001, 0.001, 0.01, 0.05, and 0.1 levels, respectively. Bright red, red, orange, and orange-yellow, and yellow denote areas with significantly higher than expected weed severity at the P = 0.0001, 0.001, 0.01, 0.05, and 0.1 levels, respectively. Green areas are neither significantly higher nor lower than expected in weed severity. Scale is 1:275,000 if map is printed as a full page.

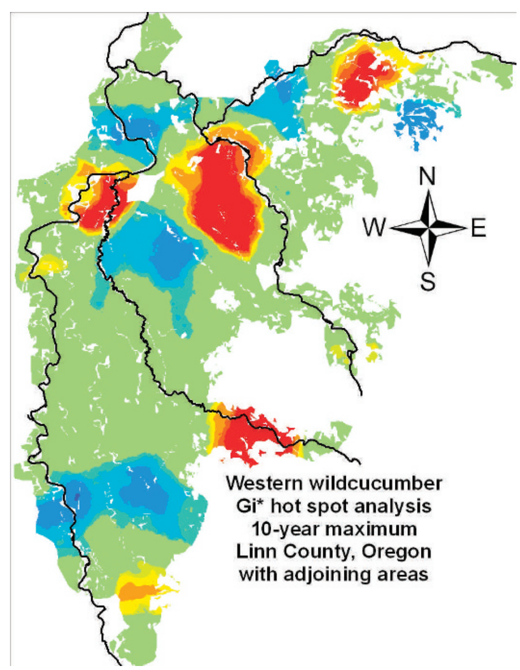


Figure 13. Gi* hot-spot analysis for 10-yr maximum severity of western wildcucumber using 4 km fixed distance neighborhood method. Dark blue, blue, light blue, dark aqua, and aqua colors denote areas with significantly lower than expected weed severity at the P = 0.0001, 0.001, 0.01, 0.05, and 0.1 levels, respectively. Bright red, red, orange, and orange-yellow, and yellow denote areas with significantly higher than expected weed severity at the P = 0.0001, 0.001, 0.01, 0.05, and 0.1 levels, respectively. Green areas are neither significantly higher nor lower than expected in weed severity. Scale is 1:275,000 if map is printed as a full page.

their severity. Although study of these factors would certainly improve our understanding of the behavior of any of the 43 weeds, greatest return on efforts would occur from study of the 10 most unique ones.

Hot spot Localization. Protection of grower privacy was an overriding concern in mapping of weed hot spots. Average number of neighboring points in Gi* calculations was 93 for a 4 km fixed distance band and 623 for a 14 km band. Because 14 km was also the median distance to peak clustering for all 43 weeds (Table 3), hot-spot probability values reflected the influence of at least seven individual fields in the Gi* analysis and 12 fields in the raster creation, and on average represented over 600 fields. Given an average grass seed field size of 18 ha, seven fields would correspond to the minimum reporting unit size traditionally used by the OSCS when aggregating production data by county, 122 ha.

For the four most strongly clustered weeds, German velvetgrass, field bindweed, roughstalk bluegrass, and annual bluegrass, neighborhood distances were set to 8, 4, 14, and 14 km in the Gi* fixed distance weighting method (Figures 8, 9, 10, and 11). German velvetgrass clearly showed a concentration in northeastern Linn County grass seed acreage, with a secondary east-west band in the southern third of the area (Figure 8). Field bindweed showed a less simple pattern, with below average severity in the northeastern region and in two areas near the center (Figure 9). Hot spots for field bindweed existed along rivers in the northern third and in far southwestern portion of the area. Annual bluegrass and roughstalk bluegrass had patterns of severity similar to each other, with a large hot spot from the center to the southwest and below average severity in the northeastern section (Figures 10 and 11). The distribution of these two weeds differed in the southwestern region, with a much more pronounced cool spot for roughstalk bluegrass than annual bluegrass. Maps for two of the perennial weeds with smallest distances for peak high/low clustering, Canada thistle and western wildcucumber, possessed several highly similar hot and cold spots, along with additional hot spots present for only one or the other of these weeds (Figures 12 and 13). Weeds with the strongest global spatial autocorrelation or high/low clustering tended to produce Gi* maps that were mainly covered by extremely high probabilities of hot spots or cold spots. Weeds with low global spatial autocorrelation or high/low clustering tended to produce maps with large areas of nonsignificance for hot spots or cold spots. Maps of all 43 weeds in JPG format at 1:275,000 scale and ArcGIS image rasters are available online at http://www.ars.usda.gov/pandp/people/people.htm?personid=4006.

The Gi* hot-spot analysis probability maps can be used by growers and consultants to determine whether specific weeds are, or are not, highly likely to occur as problems within specific fields. Fields located in areas with high probabilities of problems with specific weeds could receive more intensive scouting before relying on failure to find particular weeds in initial low intensity scouting as sufficient reason to forgo potential herbicide treatments, crop rotation practices, or seed-cleaning options. Conversely, growers with fields located in areas with low probabilities of problems with specific weeds could reduce the intensity of scouting and/or spot-spray programs for those weeds unless they already knew that their particular field had problems with a weed even though it was uncommon in the local area. The maps will also be useful in cases where rental contracts or landownership have changed, providing new managers with a ranking of which weeds were most likely to be problems in a field. Given the variation that existed within the data in the GIS, it is clear that the maps will never act as infallible predictors of where weed problems will occur. Rather they should serve as guides to help reduce the incidence of both failure to anticipate problems with specific weeds and unnecessary use of herbicides and other weed control treatments on weeds that don't truly exist within given fields.

Implications

Clustering in the distribution of grass seed weeds occurred as a consequence of both cropping history and edaphic factors, and was stronger for some weed species than others. For strongly clustered species such as German velvetgrass, field bindweed, roughstalk bluegrass, and annual bluegrass, growers and production advisors need to consider geographic location in tailoring of weed control practices to optimize resource allocation. For recently worsening problems such as wild carrot, availability of GIS data could help us understand factors contributing to this weed's spread and focus control efforts. The significant relationships between soil chemical and physical properties and weed severity on scales as coarse as soil type suggests value to incorporation of more detailed measurements of soil properties in future GIS databases. Finally, publication of maps of weed hot spots could help grass seed growers, production consultants, seed certification agencies, and seed companies more accurately monitor the impact of field production practices on weed severity. Procedures used to develop these maps maintained grower confidentiality while providing useful information to the grass seed industry.

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